International Journal of Applied Earth Observation and Geoinformation 124 (2023) 103531

Contents lists available at ScienceDirect

International Journal of Applied Earth Observation and Geoinformation

journal homepage: www.elsevier.com/locate/jag

Developing effective wildfire risk mitigation plans for the wildland urban interface

Alan T. Murray [a], Jiwon Baik [a], Vanessa Echeverri Figueroa [a], Darlene Rini [a], Max A. Moritz [b], Dar A. Roberts [a], Stuart H. Sweeney [a], Leila M.V. Carvalho [a], Charles Jones [a]

[a] Department of Geography, University of California at Santa Barbara, Santa Barbara, CA 93106, USA

[b] UC Agriculture & Natural Resources Division, Oakland, CA, US / Bren School of Environmental Science & Management, UC Santa Barbara, Santa Barbara, CA, US

ARTICLE INFO

Keywords:
Contiguity
Land acquisition
Thresholds
Wildfire resiliency planning
Vegetation management

ABSTRACT

The wildland urban interface (WUI) is a transition zone between mostly undeveloped, vegetated lands and more densely populated areas with buildings and other infrastructure. This interface is of great interest and concern in wildfire prone areas like California, as significant increases in scale, frequency and intensity of fires have resulted in devastating impacts to life-safety, property and other high value assets. Ensuring that people, property and infrastructure are safe is a major priority, but will not happen by chance. Analytical tools, risk reduction strategies and operational plans to enhance wildfire resilience, particularly in the WUI, are vital. Examples of various fire resiliency approaches involve vegetation treatment such as prescribed burns, strategic fuel breaks, fuel thinning, grazing and mastication, while other risk mitigations may include structural hardening, creation of defensible space and other measures. A challenge is selecting the best areas for wildfire risk mitigation within the WUI, among many considerations, with viable projects required to be contiguous and manageable in size. Spatial optimization has much potential for informing planning and policy efforts, enabling the formalization of goals as well as offering approaches for identifying the best solutions possible. However, underlying geographical structure and spatio-temporal characteristics are formidable obstacles in problem solution. This paper highlights geographic analytics to support mitigation initiatives within the WUI, including the use of remote sensing, topography, climate, weather, wildfire behavior simulation, parcel data, structure and infrastructure information integrated using GeoAI along with a spatial optimization model that reflects the intent to identify the best project areas. The analysis area is comprised of millions of spatial raster cells, resulting in a model with decision variables corresponding to over 26 thousand land parcels. Application results for the Santa Barbara region are detailed, demonstrating the importance of spatial optimization combined with GeoAI in strategic coordination of scarce resources to enhance wildfire resilience within the WUI.

1. Introduction

In recent decades, the increase in frequency, severity and scale of devastating wildfires within and around the wildland urban interface (WUI) have posed a significant threat to people, property, environment and other high value assets, both during the fire as well as post-fire due to flooding, debris flows, landslides, etc. In addition to the direct and more measurable impacts to individuals and communities, catastrophic wildfires have numerous short- and long-term secondary impacts to social capital, livelihoods, environmental services, public health (e.g., poor air and water quality, trauma), as well as disrupt supply chains and worker productivity in local and regional economies. These impacts are likely to worsen as fires in the WUI are anticipated to increase due to ongoing pressures for urban housing expansion, accumulation of biomass from historical fire exclusion practices, and greater fire danger days and extreme weather conditions due to climate change (Thompson et al. 2010, Schoennagel et al., 2017, Radeloff et al., 2018). That said, while wildfires can have a devastating impact on the human-environment system, it also plays an essential role in natural ecological processes in many bioregions, contributing to vegetation regeneration, soil and mineral replenishment as well as pest, insect and invasive species control. Given the range of benefits fire offers the natural environment and associated human services, developing wildfire risk mitigation plans based on co-existence strategies presents increased opportunities to lessen the impacts of wildfires on life-safety and property as well as live with fire in a more sustainable and cost-effective way

E-mail address: amurray@ucsb.edu (A.T. Murray).

https://doi.org/10.1016/j.jag.2023.103531
Received 5 June 2023; Received in revised form 2 October 2023; Accepted 18 October 2023
Available online 26 October 2023

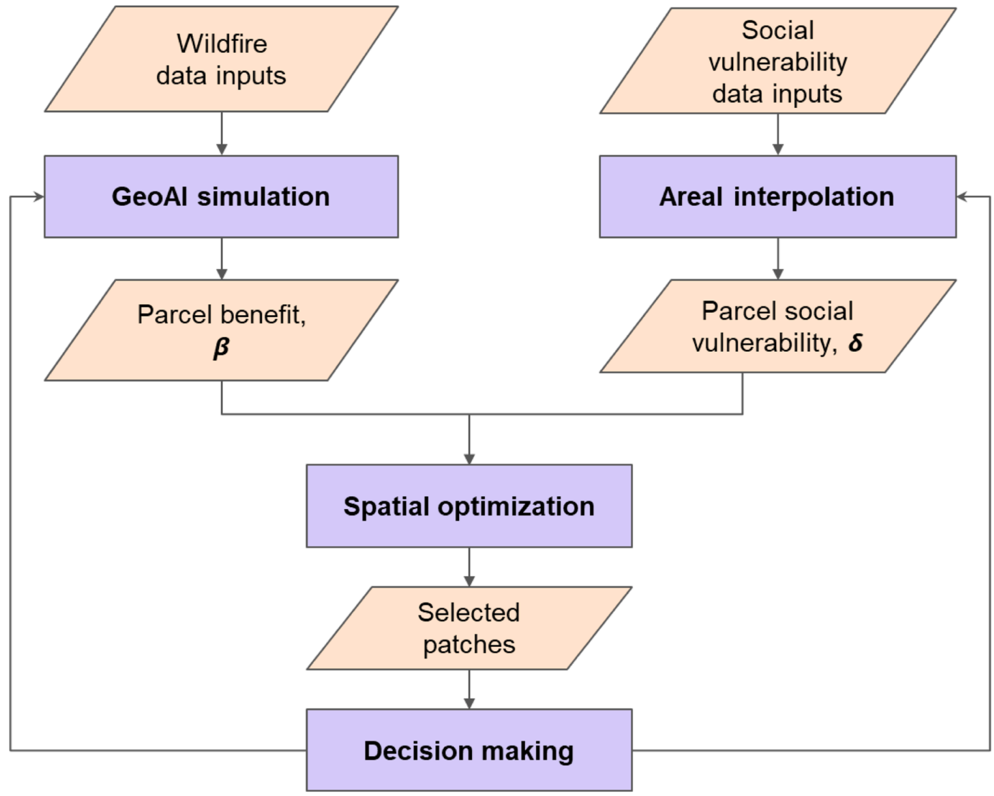

Fig. 1. Spatial analytical framework.

(Moritz et al., 2014).

Developing co-existence strategies, however, necessitates a more diverse and comprehensive understanding of the range of hazards, risks, vulnerabilities and benefits of wildfires on the human-environment system, as well as requires methods and tools to help prioritize, plan and operationalize wildfire resiliency programs from a more holistic perspective. Existing wildfire resiliency planning approaches and strategies primarily stem from a perspective centered on wildfire hazards, firefighting response and land resource management (Manzello et al., 2018), oftentimes resulting in policies and programs that emphasize hazard-focused mitigations (e.g., fuel treatments, vegetation management, firefighting technologies, ignition prevention) at national, state and county scales. While hazard mitigation is a key component to managing WUI fire risk, it typically does not capture the diversity and range of assets and performance objectives that individuals and communities value, nor does it integrate the variety of geographic vulnerabilities and coping capacities at the community- or neighborhood-scale (Calkin et al., 2013). It is well known in disaster risk management and development studies that individual and community-level vulnerabilities are central to risk, and that vulnerable populations are disproportionately impacted by disasters (Wisner et al., 2004). That is, some populations and communities are more susceptible to the impacts of wildfire due to access and functional needs as well as mobility and communication limitations, but also from poorly designed and constructed structures (Wigtil et al., 2016). Thus, understanding, integrating and evaluating wildfire risk from hazard, exposure and vulnerability perspectives are central to developing wildfire resiliency strategies that prioritize mitigation in more holistic terms in order to balance a complex set of community values.

Decreasing wildfire risk in the WUI, however, will not happen by chance. Planning methods and tools are needed to support adaptive resilience goals and objectives, such as those advocated by Schoennagel et al. (2017) and others. CAL FIRE (California Department of Forestry and Fire Protection) too seeks to assess and identify risk mitigation actions, especially forest restoration and prescribed fire, that will contribute to the California Forest Carbon Plan, part of the Fire and Resource Assessment Program. Federal and state governments in the US have allocated billions to mitigate wildfire risk (Schoennagel et al., 2017), with recent emphasis on the WUI. The focus of this paper is identifying priority areas for wildfire risk mitigation efforts. This includes vegetation management, structure and infrastructure hardening, land-use zoning and integrated community defensible space (e.g., natural or man-made fuel breaks, agricultural belts, green open spaces). The next section offers background on modeling to support strategic risk mitigation planning. This is followed by a review of spatial analytics, including GIS, GeoAI and spatial optimization for wildfire risk mitigation design. Then a case study of the WUI in the coastal region of Santa Barbara is provided. The paper ends with discussion and conclusions.

2. Background

There are a number of different research efforts in land use design and management to support strategic mitigation. This has largely involved the use and application of spatial optimization models and supporting solution approaches. Spatial optimization in land use and forest management has a long and distinguished history. Particularly noteworthy is the work of Wright et al. (1983) focused on land acquisition along with the forest management models reviewed in Hof and Bevers (1998).

Land acquisition was characterized by Wright et al. (1983) as involving the selection of the best parcels to form an area, seeking a contiguous collection of parcels limited in total size. Much research has followed seeking to solve and extend this basic planning problem, including that of Williams (2002), Shirabe (2005), Onal et al. (2016) and Murray et al. (2022). Yao et al. (2018) and Xiao and Murray (2019) offer recent reviews of different land acquisition problems. In support of wildfire risk mitigation, Ager et al. (2013) is noteworthy, applying a heuristic approach to identify land acquisition solutions in what is now known as ForSys. Subsequent research by Murray et al. (2022) and Murray and Church (2023) offer formal specification and exact solution of the land acquisition problem outlined in Ager et al. (2013).

Forest management has long been supported by spatial optimization, particularly through the efforts of the USDA Forest Service (see Kent et al., 1991). A number of interesting modeling approaches have been proposed and applied since then to address a range of management issues, including wildfire risk mitigation. Wei et al. (2008) specified a loss minimization problem coupled with wildfire simulation to identify vegetation treatment areas. Kim et al. (2009) devised a heuristic, the great deluge algorithm, for fuel treatment. Chung et al. (2013) sought to minimize loss through the application of simulated annealing coupled with wildfire simulation to identify the location and timing of fuel treatment. Recent work by Pludow and Murray (2023) extends a knapsack optimization approach to include dispersion and spatial spillover implications in wildfire risk mitigation at a neighborhood level.

Much research has followed the initial developments of Ager et al. (2013), applying and extending ForSys (see Pludow et al., 2023). Recently, Ager et al. (2021) applied ForSys combined with clustering and wildfire simulation for forest restoration and risk reduction. As noted previously, there has also been considerable attention given to exact spatial optimization approaches to identify contiguous mitigation areas, including that of Murray et al. (2022) and Murray and Church (2023). Important challenges remain in supporting wildfire risk mitigation planning that involves geospatial big data, particularly with respect to integration with GeoAI as well as spatial optimization.

3. Spatial analytics

There are a range of spatial analytics that may be used to support evaluation, planning, management and policy efforts. Reviews can be found in O'Sullivan and Unwin (2010 (O'Sullivan and Unwin, 2010)), Murray (2010, 2021) and Rogerson (2020), among others. In this research, an integrated framework using geographic information system (GIS), geospatial artificial intelligence (GeoAI) and spatial optimization is proposed to support wildfire risk mitigation as outlined in Fig. 1.

GIS involves hardware and software that support spatial data collection, management, manipulation, analysis and display (Longley et al., 2015). Combined with remote sensing and GPS (global positioning system), the relevance and significance of GIS has never been greater with mapping at the heart of services relied upon daily by virtually every human being. Fig. 1 highlights spatial integration and manipulation within the framework, including aggregation of cell level information to parcels and areal interpolation of attributes from incommensurate spatial units.

GeoAI represents the evolution of how Smith ((Smith, 1984)) as well as others in geography recognized the inevitable integration of artificial intelligence in geographic planning and management processes. Li (2020) characterizes GeoAI as involving analytics to deal with geospatial big data through extended artificial intelligence and high-performance computing approaches. In essence, GeoAI reflects the emergence of many methods that can be used in interesting ways to elicit insights about structure and knowledge, both spatial and aspatial. Broadly speaking, GeoAI includes various classification, clustering and prediction approaches, such as artificial neural networks, cellular automata, heuristics, spatial data mining, spatial clustering and knowledge graphs as well as natural language processing techniques. Recent work in GeoAI refers to the adoption or adaptation of data-driven deep learning techniques (either explicitly or implicitly) for spatial data. Fig. 1 notes the reliance on GeoAI to simulate wildfire hazards.

Spatial optimization involves "structuring and solving a problem to identify the best decisions that conform to imposed restrictions, where some combination of decisions, coefficients, functions, relationships and/or constraints are geographic" (Murray 2023). Overviews of spatial optimization may be found in Church (2001), Tong and Murray (2012), Cao (2017) and Murray (2023), highlighting inherent characteristics, classic approaches and solution techniques. As the above definition suggests, key components of spatial optimization are: decisions to be made, criteria to be optimized, conditions that must be met or maintained and the capability to derive good solutions. Often, mathematical notation and formalization is used to specify a spatial optimization problem, but this may also be done through descriptions, flowcharts and programming code (or pseudo code). Based on this, a heuristic or exact approach may be applied to solve the problem. Such specification and the capability of representing important relationships, conditions and goals is precisely what makes spatial optimization invaluable. Further, Murray (2021) discusses that the ability to establish significance through exact solution methods is particularly critical. Fig. 1 indicates that the proposed framework relies on spatial optimization to identify the best wildfire risk mitigation options.

As discussed above, elements of GIS, GeoAI and spatial optimization are integral components of the proposed spatial analytical framework in Fig. 1, but also can be more precisely communicated and formalized in support of wildfire risk mitigation efforts. Consider the following:

i = index of parcels.
β_i = benefit of wildfire hazard mitigation to parcel i
δ_i = social vulnerability of parcel i
α_i = area of parcel i
p = number of risk mitigation areas to be identified
Φ_i = set of parcels that neighbor parcel i
τ = average size maximum for migration area

Most of this notation is self-explanatory, with a focus on parcels as the decision-making unit, but further discussion of β_i and δ_i is important to offer broader context for this research. β_i reflects the benefit to area i from a particular wildfire risk mitigation strategy. Wildfire hazard is primarily a function of local topography, vegetative fuels, ignitions and weather. Mathematically, this can be generalized as $\beta_i = f(\textit{topography}, \textit{fuels}, \textit{ignitions}, \textit{weather}, \textit{fire spread}, \textit{land use}, \ldots)$, where $f(.)$ is a defined function based on the input variables and conditions. Given that there is much uncertainty in local conditions at any given time, the benefit of mitigation can be estimated using GeoAI through simulation. Indeed, there are a range of software packages, libraries and other open-source code to carry out wildfire simulation, such as FlamMap, LandFire, FIRETEC, QES-Fire, Wildfire Analyst, FSim, FSpro, MEDFIRE, and others. Wildfire simulation involves the creation of virtual scenarios that mimic real-world fire spread based on topography, fuel load, weather and other characteristics. By simulating and evaluating wildfire behavior and potential impact on parcels, associated benefit of wildfire risk mitigation can be derived. Simulation provides valuable insights into the potential threat of wildfires in terms of their spatial extent, intensity, and areas most susceptible to impact. Social vulnerability, δ_i, to wildfire too is a function of many characteristics and conditions. Mathematically, this may be generalized as $\delta_i = g(\textit{age}, \textit{mobility}, \textit{demographics}, \textit{access}, \textit{accessibility}, \textit{wealth}, \textit{etc.})$, where $g(.)$ is a defined function based on the input variables and conditions. The combined conditions of wildfire risk and social vulnerability make for important considerations in mitigation efforts. More discussion of β_i and δ_i specification and utilization is offered later in the paper.

Decision variables are as follows:

$$X_i = \begin{cases} 1 & \text{if parcel } i \text{ is selected for inclusion in mitigation area} \\ 0 & \text{otherwise} \end{cases}$$

$$V_i = \begin{cases} 1 & \text{if parcel } i \text{ is categorized as mitigation area sink} \\ 0 & \text{otherwise} \end{cases}$$

Y_{ij} = accumulated flow from parcel i to j destined for mitigation area sink

The most significant decision variable is X_i, indicating which parcels are to undergo wildfire risk mitigation efforts. The other decision variables, V_i and Y_{ij}, are needed within the model to impose contiguity

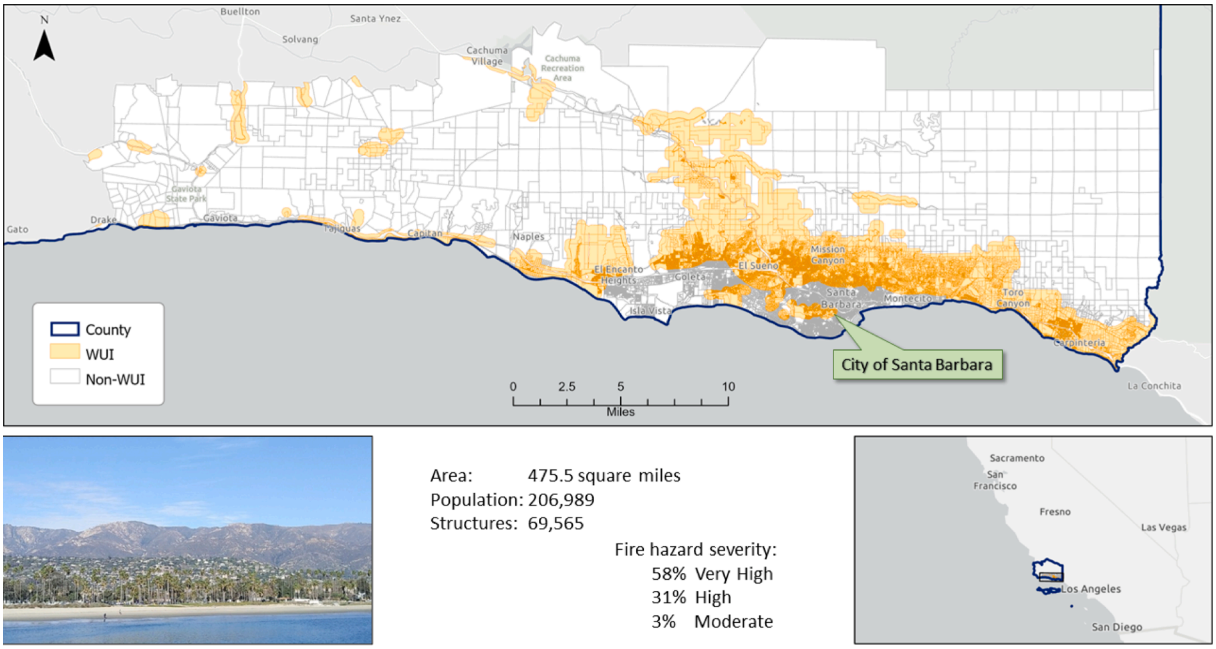

Fig. 2. Front range foothill region of Santa Barbara County, CA, indicating parcel boundaries, along with WUI and non-WUI areas.

conditions as a network flow problem. Further description is offered below.

The intent in this research is to delineate a prespecified number of wildfire risk mitigation areas, p, where individual areas must be comprised of a contiguous set of selected parcels, e.g., $X_i = 1$, and maintain a maximum size limitation, τ. In this case, the focus is on wildfire hazards and social vulnerability simultaneously to help identify and prioritize areas for risk mitigation, such as landscape level vegetation treatment, structural hardening and creation of defensible space. The formulation of this problem is an extension of the approach proposed in Murray and Church (2023), where wildfire hazard benefit, β_i, and social vulnerability, δ_i, are simultaneously considered.

$$Maximize \sum_i \beta_i X_i \tag{1}$$

$$Maximize \sum_i \delta_i X_i \tag{2}$$

$$Subject\ to \quad \sum_i V_i = p \tag{3}$$

$$\sum_{j \in \Phi_i} Y_{ij} - \sum_{j \in \Phi_i} Y_{ji} \geq \alpha_i X_i - \tau V_i \quad \forall i \tag{4}$$

$$\sum_{j \in \Phi_i} Y_{ij} \leq \tau X_i \quad \forall i \tag{5}$$

$$V_i \leq X_i \quad \forall i \tag{6}$$

$$X_i \in \{0, 1\} \quad \forall i \tag{7}$$

$$V_i \in \{0, 1\} \quad \forall i$$

$$Y_{ij} \geq 0 \quad \forall i, j$$

The objective, (1), seeks parcels that offer the greatest benefit in mitigating potential wildfire hazards. Objective, (2), seeks parcels that would protect the most socially vulnerable. Constraints (3) specify that p treatment areas are to be identified. Constraints (4) initiate flow from selected parcels as well as limit total flow destined to each selected sink. Constraints (5) bound flow out of parcel i to be no more than the maximum, or zero if not selected. Constraints (6) link sink and parcel selection. Constraints (7) impose binary and non-negativity conditions on decision variables.

Again, this is an extension of the model introduced in Murray and Church (2023) that considers multiple objectives. The formulation is novel due to the use of an underlying network structure where flow initiated by selected units is limited to only neighboring units that are also selected, with all flow terminating at a selected sink of an individual treatment area. Proof of constraint validity for the purposes of forming contiguous areas that adhere to size limits can be found in Murray and Church (2023). Solution of this formulation is possible using commercial mixed-integer programming software. There are, however, two complicating factors. One is that problem application sizes that can be addressed in practice may be limited, with previous work considering only hundreds to a few thousand land units. In some cases optimality gaps remained after solution time limits were reached, but the gaps were considered relatively small. A second issue involves model solution when there are multiple objectives. The existence of multiple, likely competing, objectives means that there is no single optimal solution, but rather a set of Pareto tradeoff solutions representing compromise alternatives with respect to the various objectives. Cohon (1978) discusses a number of approaches for identifying the tradeoff solution set, with the weighting method being particularly popular and the constraint method being preferred when the set is non-convex due to integer requirements. For the weighting method, the introduction of a priority weight, w, can be used to integrate objectives (1) and (2) as follows:

$$Maximize w \sum_i \beta_i X_i + (1 - w) \sum_i \delta_i X_i \tag{8}$$

where $w \in [0, 1]$. For any value of w, (3)-(8) may be solved, with unique solutions representing tradeoff alternatives. The so called Pareto or tradeoff set can be derived assuming that incremental changes to w within the range are sufficiently small.

An alternative is the constraint method, where one or more objectives are effectively moved to model constraints. Consider for example objective (2) along these lines:

$$\sum_i \delta_i X_i \geq \Psi \tag{9}$$

Table 1
Geographic data sources.

Model coefficient	Data	Resolution	Source
–	California Wildland Urban Interface	400 *m*	CAL FIRE
i	Santa Barbara parcels	Parcel	SB County
β_i	Elevation, slope, aspect, fuel model, canopy cover, stand height, canopy base height, canopy bulk density	30 *m*	LANDFIRE 2020
δ_i	Social vulnerability	1 km	NASA SEDAC
	Social vulnerability	Block group	Bryan (2022)

Table 2
Parcel attribute summary statistics.

	Area (acres)	Mitigation benefit	Social vulnerability
Mean	2.44	4.81	0.64
Standard deviation	13.60	33.58	4.54
Minimum	0.00	0.00	0.00
Maximum	493.94	1285.90	284.10

The right hand side value, Ψ, can be set and the resulting model, (1), (3)-(7) and (9), solved. If a range of values, $\Psi \in [min, max]$, are considered, then the tradeoff set can be derived assuming that incremental changes to Ψ within the range are sufficiently small to ensure all tradeoff solutions are found.

Of course, irrespective of the weighting method or the constraint method being relied upon, the implication is that many individual problems will need to be solved, one for each unique value of w or Ψ, which may be hundreds, thousands or more in number. This is clearly an issue when a single problem instance is itself extremely challenging to solve.

4. Study area

The area of focus in this research is the south-facing coastline of Santa Barbara County, California shown in Fig. 2, roughly bounded by the City of Carpinteria to the east, the Gaviota State Park to the west, the Santa Ynez Mountain Range to the north and the Pacific Ocean to the south. The area also includes the City of Santa Barbara - the population and cultural seat of the county - as well as the City of Goleta and the communities of Summerland, Montecito, Isla Vista and other unincorporated lands. Covering a total area of 475.5 square miles, this coastal region has a 2020 Census population of 206,989 with primarily agricultural (77 %) and residential (6.3 %) land uses followed by other secondary uses such as open space (9.5 %), recreation (1.2 %), utility (0.3 %), industrial (0.13 %) and commercial zones (0.08 %) (County of Santa Barbara, 2023).

Given its geographic location, topography and land uses, the study area and surrounding lands have an extensive history of large catastrophic wildfires and post-wildfire debris flows (Murray et al., 2021, Zigner et al., 2022) that have resulted in devastating impacts to life safety, health, the built environment, local economies, the natural environment and cultural/historical resources, particularly in the WUI. This is expected to continue in the foreseeable future as roughly 98 % of the study area is located within High or Very High fire hazard severity zones, and eight cities / communities designated as "Communities at Risk '' by the California State Forester. Within this region (see Fig. 2), 37 % of the area is designated as WUI (i.e., interface, intermix and influence zones per CAL FIRE) where some 50 % of the population resides. High fire risk is due to a combination of rugged, steep mountain terrain, narrow canyons, hot/dry Mediterranean climate with seasonal Sundowner winds (Jones et al., 2021), and large uninterrupted wildlands dominated by dense chaparral (Murray et al., 2021, Zigner et al., 2022).

The area has many neighborhoods of high population density, but also vulnerabilities associated with access-functional-needs, limited English proficiency, fixed-income, elderly and low-income populations that are more likely to have limited capacities to prepare for, respond to, and/or recover from a major wildfire incident. An estimated 30 % of the population speaks a language other than English at home (US Census Bureau, 2021). Approximately 10.2 % of the population has some form of disability (i.e., hearing difficulty at 2.3 %, vision difficulty at 2.1 %, cognitive difficulty at 4.8 %, ambulatory difficulty at 4.7 %, self-care difficulty at 2.1 % and independent living difficulty at 4.5 %). Other vulnerable groups in the study area include populations under 5 years of age at 4.8 %, those 65 years and older are 15.9 %, and people living in poverty at 15.7 % of the total population.

The unit of analysis in this research is the parcel given wildfire risk mitigation planning and decision-making needs, with 41,087 total parcels and 26,326 parcels specifically within the WUI (see Fig. 2).

5. Application results

Supporting geographic information for the analysis that follows is summarized Table 1, including details on what model coefficient they contribute/relate to, the spatial resolution and source. The WUI layer was obtained from the California Department of Forestry and Fire Protection. Parcel data for Santa Barbara was provided by Santa Barbara County, but is not publicly available. FlamMap simulations relied on topological and vegetation data sourced from LANDFIRE 2020 (version 2.2.0), serving as the basis for wildfire mitigation benefit, β_i. Social vulnerability data was obtained from NASA (Socioeconomic Data and Applications Center) as well as from Bryan (2022). The derived social vulnerability measure, δ_i, was a spatially weighted average of these two inputs. Further details on data processing and parameter estimation follow.

As noted previously, the intent of this analysis is to identify and help prioritize wildfire risk mitigation initiatives (e.g., vegetation treatment, structural hardening, creation of defensible space) when considering both hazards and social vulnerability. Two critical components of the analytical framework for wildfire risk mitigation efforts are derivation of benefit and social vulnerability. Estimation of β_i, wildfire hazard mitigation benefit, is achieved using GeoAI through FlamMap simulation,[1] with an output being minimum travel time of fire through a region. The simulation frames fire growth modeling as finding the shortest time to move between specific points in a two-dimensional network. The paths that minimize travel time between these points are then used to determine the fire perimeter at a given moment in time. This method yields fire perimeters and related characteristics like spread rate and conditional flame length (Finney, 2002). The byproduct can be summarized as the wildfire hazard β_i. This approach leverages GeoAI capabilities by applying complex computational and analytical models to predict fire spread across diverse geographical landscapes. The simulation takes into account various types of spatial data, such as terrain, vegetation and weather conditions, to mimic fire behavior. This spatially-explicit predictive modeling of fire spread is key, underscoring how AI approaches can be utilized to understand, manage, and mitigate environmental hazards. The simulation uses 30x30 m cells to model wildfire spread under various conditions, enabling hazard mitigation benefit to be derived through aggregation to the parcel based on conditional flame length and burn probability as outlined in the Appendix A.

Estimation of social vulnerability, δ_i, is based on existing information for block groups and 1x1 km grids. Social vulnerability is a byproduct of

[1] FlamMap (6.2) relies on LANDFIRE, a system that manages data on vegetation, fuel and disturbance, for wildfire behavior modeling.

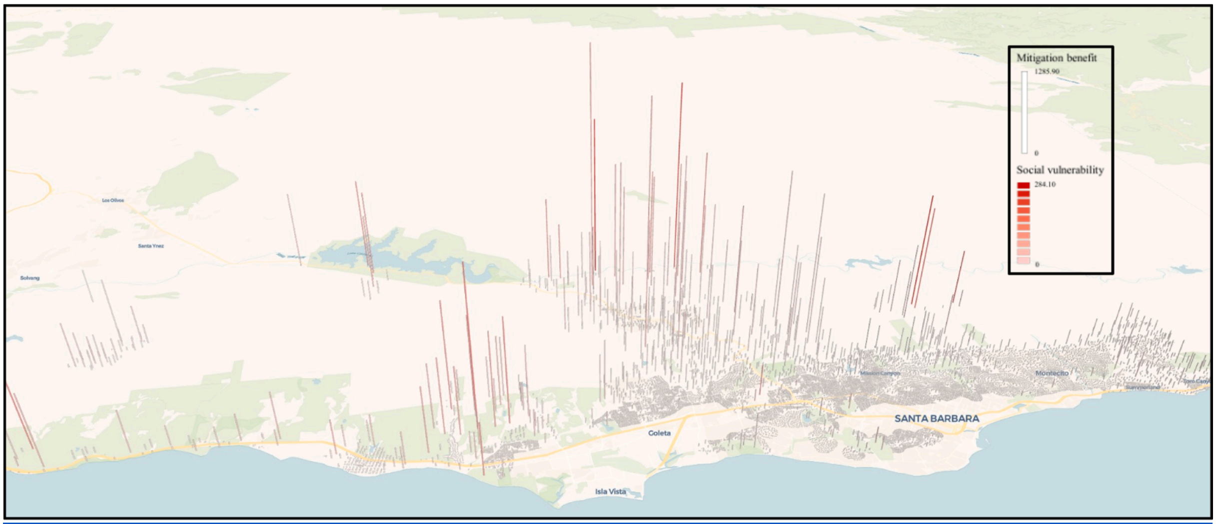

Fig. 3. Interactive visualization depicting the spatial distribution of wildfire hazard mitigation benefit β_i and social vulnerability δ_i(an interactive display can be found at: https://wri.ucsb.edu/sites/default/files/2023-05/weighted_ih_svi.html).

Table 3
Summary of bi-objective results for different treatment area scenarios.

Treatment area (acres)	Number of treatment areas	Non-dominated solutions found	Best benefit objective	Best social vulnerability objective	Average optimality gap	Average solution time (sec)	Step (ε)
50*	1	27	224.03	42.64	9.44 %	6,199.30	0.609
50	60	26	9,574.29	1,126.07	7.84 %	3,601.47	25.508
50	130	21	18,314.11	2,073.92	4.68 %	3,601.56	47.08
100*	1	8	415.62	175.27	11.36 %	9,146.04	1.121
100	30	22	10,273.77	1,107.85	5.13 %	3,597.06	26.354
100	64	18	19,916.53	2,139.26	7.50 %	3,601.07	47.507
150	1	8	596.74	109.19	10.11 %	2,537.82	1.560
150	20	26	10,443.97	1,422.57	5.93 %	3,601.95	26.419
150	42	18	20,227.42	2,098.31	5.08 %	3,601.63	49.91

* Processing time limit increased to 3 h for this scenario.

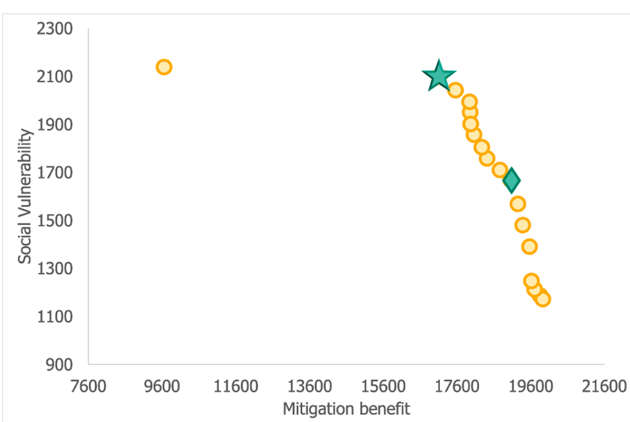

Fig. 4. Pareto frontier for 64 treatment areas scenario (100 acre maximum).

many factors that influence the ability of a person to prepare for, respond to and recover from wildfire threats, including age, income, mobility and language, as noted previously. Since this information is not readily available at the parcel level, it must be estimated in some manner. Existing work on social vulnerability has produced block group and 1x1 km grid estimates in the region, based on which δ_i is derived in this research. Details on how this is done are given in the Appendix A.

A parcel level summary of wildfire hazard mitigation benefit and social vulnerability is given in Table 2 for the 26,326 parcels in the WUI.

The mitigation benefit and social vulnerability parcel attributes are interpreted as per acre quantities. Fig. 3 displays a 3-D visualization of the spatial distribution wildfire hazard mitigation benefit and social vulnerability. Each bar represents a parcel, with the height reflecting mitigation benefit (higher bar indicating higher benefit) and the hue of reds indicating social vulnerability (darker red indicates a higher social vulnerability).

A Jupyter Notebook (Python 3.7) interface was utilized to carry out all data processing, manipulation, optimization and visualization. GUROBI 9.5 was called to solve all optimization problem instances on a desktop personal computer (12th Gen Intel® Core™ i7-12700 k, CPU of 3.61 GHz, 32 GB RAM) running Windows 10 (64-bit). In general, each problem instance was given a maximum of one hour (3600 s) for solution. In most cases there is an unresolved optimality gap due to the solution time limit, indicating the theoretical bound on solution quality for the identified solution. Note that two scenarios did permit problem solution to extend up to three hours given observed average optimality gaps.

The constraint method was applied to obtain model solutions. The value of Ψ began with a minimum value, then the problem was solved. Ψ was then increased by ε and the new problem solved. This continued until Ψ reached a maximum value. For each scenario, the range and increment of ε translated to 71 problem instances being solved. Table 3 summarizes the results obtained from the bi-objective spatial optimization approach using the constraint method. Three different treatment area sizes of 50, 100, and 150 acres were considered. Additionally, a range in the number of treatment areas was also considered. This offered

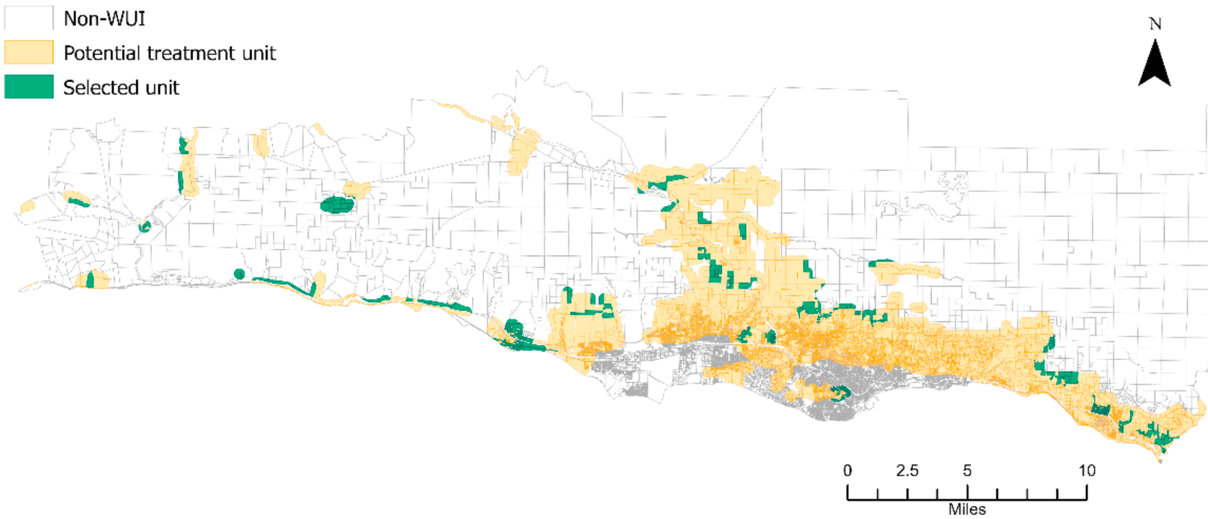

Fig. 5. One tradeoff solution (star in Fig. 4) showing areas within the WUI for wildfire risk mitigation (64 treatment areas, with maximum size of 100 acres).

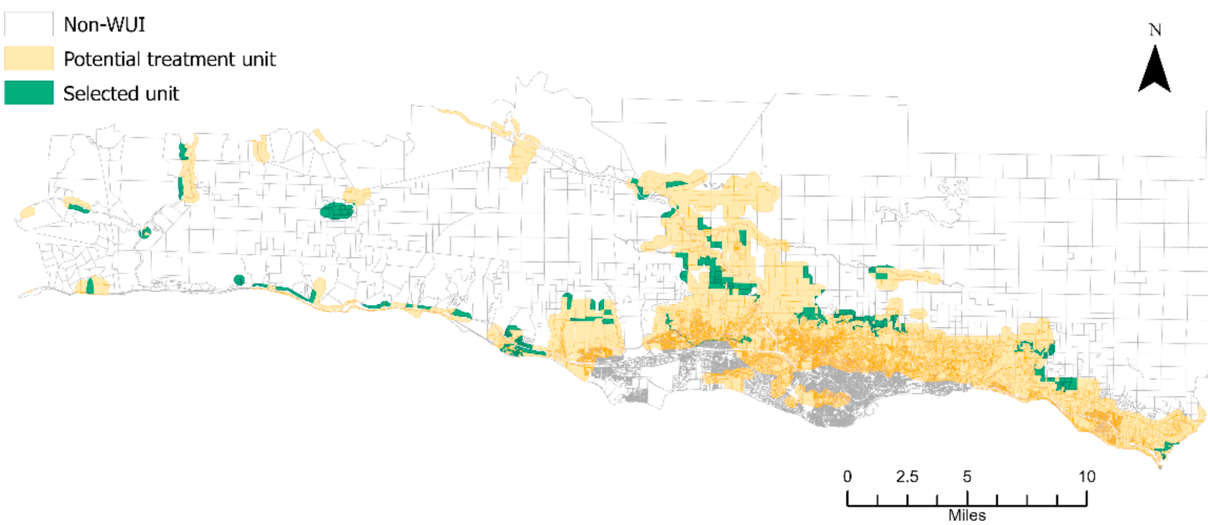

Fig. 6. Alternative tradeoff solution (diamond in Fig. 4) showing areas within the WUI for wildfire risk mitigation (64 treatment areas, with maximum size of 100 acres).

Table A1
Integrated Hazard determination.

Integrated hazard		Burn probability 0–20 % of max	20–40 % of max	40–60 % of max	60–80 % of max	80-100 % of max
Conditional flame length	> 12 ft	4	4	5	5	5
	> 8–12 ft	3	3	4	4	5
	> 6–8 ft	2	3	3	4	4
	> 4–6 ft	2	2	3	3	4
	> 2–5 ft	1	1	2	2	3
	> 0–2 ft	1	1	1	2	2

(Source: US Department of Interior, 2023).

a variety of decision-making scenarios. Table 3 reports for each scenario the number of non-dominated solutions found, the best benefit objective found, the best social vulnerability objective found, the average solution times, and the step applied.

There are a number of important observations for the scenarios in Table 3. First, there are generally many tradeoff solutions for each scenario, ranging from eight identified for the scenario of treatment area of 150 acres (one treatment area) and 27 in the case of treatment area of 50 acres (1 treatment area). The average optimality gap of 10.11 % and 9.44 %, respectively, suggests that optimal solutions could not be confirmed in all cases, but established solution quality is likely sufficient for analysis, planning and management purposes in this particularly application context.

Each reported scenario in Table 3 can be visualized in terms of the associated tradeoff solutions found. Fig. 4 depicts the tradeoff curve of solutions for the case of 64 treatment areas with a size of no more than 100 acres each. In this case, there are 18 non-dominated solutions, reporting a 7.50 % optimality gap across the 71 problem instances solved.

Each solution in Fig. 4 has a corresponding unique spatial configuration associated with it. The solution marked with a star in Fig. 4 is

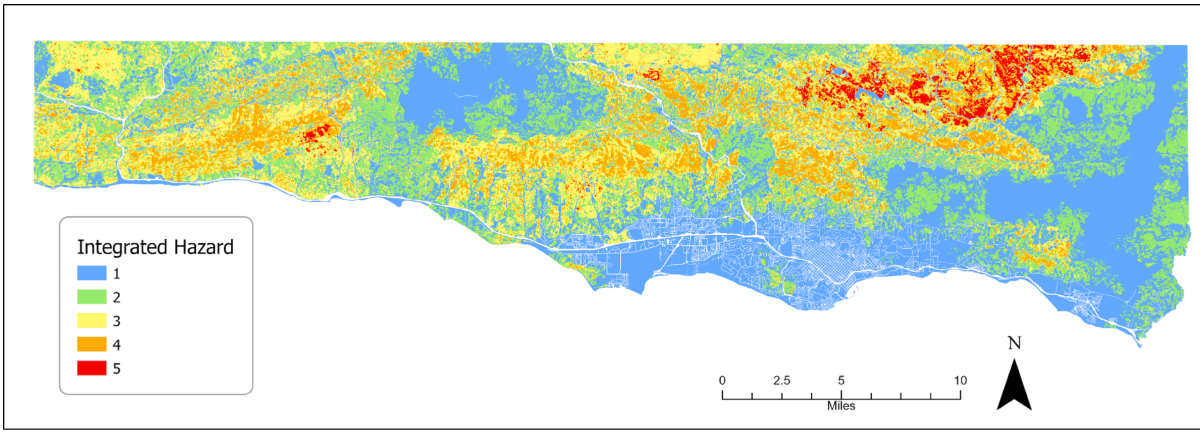

Fig. A1. Wildfire hazard mitigation benefit derived using FlamMap simulation.

Table A2
Validation and cross check of areal interpolation to derive parcel level social vulnerability.

Areal interpolation source	Ground truth	RMSE	Mean RMSE
Block Group	Block Group	0.137	0.11
Block Group	1 km Grid	0.083	
1 km Grid	Block Group	0.168	0.108
1 km Grid	1 km Grid	0.047	
BG and Grid	Block Group	0.087	0.073
BG and Grid	1 km Grid	0.058	

shown in Fig. 5. This configuration represents an important tradeoff that favors social vulnerability more than hazard benefit, but still achieves a relatively high degree of risk mitigation benefit. Specifically, this configuration is within 2.19 % of the maximum possible total social vulnerability benefit and within 14.1 % of the maximum possible total hazard benefit. The highlighted units in Fig. 5 are selected for proactive wildfire risk mitigation initiatives considering vulnerable communities. The selected parcels primarily correspond to several areas along the foothills of the Santa Ynez mountains, encompassing a portion of Mission Canyon, north of Mission Canyon, Toro Canyon, and north of Carpinteria. Other treatment areas were selected along the 101 highway around El Capitan, Tajiguas, and Lento, and at the Goleta highlands, around Winchester Canyon. These areas do indeed exhibit a high degree of social vulnerability, yet offer substantial benefit in reducing wildfire hazards.

An alternative tradeoff solution marked with a diamond in Fig. 4 is shown in Fig. 6. This configuration represents a tradeoff that favors hazard risk mitigation benefit more than social vulnerability, but still achieves a relatively high degree of social vulnerability benefit. Specifically, this configuration is within 4.37 % of the maximum possible total hazard benefit and within 21.95 % of the maximum possible total social vulnerability benefit. Fig. 6 highlights the subtle differences and nuances compared to the configuration shown in Fig. 5, and as a result of these differences greater hazard risk benefit can be achieved but does so with less social vulnerability benefit.

6. Discussion

There are a number of items deserving of further discussion and attention. Firstly, it is challenging to accurately characterize wildfire behavior, particularly in the WUI. This is attributed to limitations in understanding the composition, distribution and other features of fuels in the built environment and their associated influence on fire rate of spread, heat release rates, etc. at different scales, in combination with varying environmental and meteorological conditions. Urban/developed fuel models, such as fuel code NB1 (91) in FlamMap, generally represent material in the built environment (e.g., concrete buildings, steel structures or asphalt pavement) as noncombustible. This is a well-known limitation in current wildfire behavior models (simulation) as urban areas contain significant sources of fuel that can burn, leading to urban conflagration. Such incidents usually involve structure-to-structure ignition or ignition caused by firebrands, which are not well captured by wildfire behavior fuel models (Scott and Burgan, 2005). Local factors, such as the presence of flammable and combustible materials, natural and ornamental vegetation and other specific conditions within the urban environment, contribute to fire spread and further

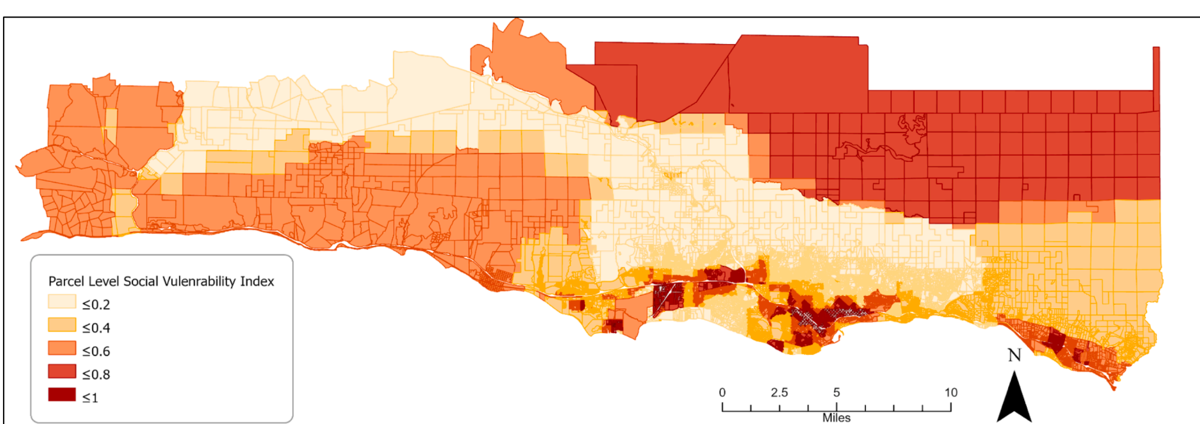

Fig. A2. Parcel level social vulnerability.

increase the risk of ignition. Therefore, it is crucial to carefully evaluate the assumptions and limitations of current wildfire behavior models and consider additional factors when interpreting simulation results in the context of urban regions. Other well-known factors in wildfire behavior and risk include live fuel moisture, fire-atmosphere coupling, boundary layer dynamics and downslope winds such as Sundowners winds (Blier, 1998, Carvalho et al., 2020, Jones et al., 2021, Murray et al., 2021, Zigner et al., 2022). Accurately accounting for these in simulation models can be difficult, yet their omission can result in underestimating risk.

Secondly, defining and interpreting social vulnerability in the context of wildfire risk also presents challenges. Social vulnerability is oftentimes used as a proxy to identify individuals and communities that are more prone to disproportionate impacts due to disasters (see Bakkensen et al., 2017). In the case of wildfire risk, internal validity of what constitutes social vulnerability is not well established at fine geographic scales. General interpretations based on fairly coarse spatial definitions (e.g., Census Tract) are potentially problematic, but also difficult to disaggregate to practical decision-making units like a parcel. There is ongoing research interested in improving estimates of social vulnerability (see Spielman et al., 2020). The important point, however, is that a degree of uncertainty no doubt exists in social vulnerability measures, δ_i, making this an important area for future research.

Thirdly, it is important to note that in the context of our study, the optimization outcomes are intricately linked to input parcel benefit and social vulnerability factors. This interdependency makes consideration of the potential implications of input parameter variability, β_i and δ_i, important. When it comes to parcel wildfire mitigation benefits, a crucial aspect of sensitivity analysis centers on topological and meteorological parameters. These variables have the potential to introduce variations into the results of GeoAI simulations. It is recognized that the use of different sets of randomly selected ignition points in simulations may also affect outcomes. Regarding social vulnerability, optimization results can also be influenced by social vulnerability specification, as noted above. The work reported here utilized a spatially weighted mean derived from 1x1 km and block group social vulnerability estimates. The nuances in input parameter specification, both for benefit and vulnerability, underscore the need for a comprehensive examination of how mitigation results are influenced by relied upon model inputs.

Finally, there are clearly many important issues that remain to be addressed associated with spatial optimization model solution. First, the integration of two or more objectives, where the prioritization is to mitigate wildfire risk in socially vulnerable communities has been demonstrated, but identifying Pareto tradeoffs and successfully solving corresponding model instances is not trivial. The reported results in Table 3 indicate remaining optimality gaps, reflecting that individual problem instances are indeed difficult to solve. Requiring the repeated solution of problem instances to identify tradeoffs makes this an even greater challenge. Murray and Church (2023) report an observed optimality gap of 1.6 % across the 34 problem instances evaluated (allowing one hour of processing for each problem instance), with the largest problem involving 10,642 spatial units. However, they only addressed a single objective problem. For the scenarios considered in this paper where only a single objective is included, e.g., (1), (3)-(7) or (2)-(7), the observed average optimality gaps were 2.73 % using objective (1) and 3.84 % using objective (2). This is slightly higher than what was reported in Murray and Church (2023), but the problem size is 261 % larger in this paper involving 26,326 parcels. Thus, this is fairly consistent with what one might expect. However, what is observed in Table 3 is substantially more difficult, suggesting that the constraint method alters model structure to negatively impact solvability properties. For this reason, larger optimality gaps are encountered. This suggests that enhanced solution approaches for multi-objective problems like (1)-(7) are an important future research need.

7. Conclusions

This paper highlighted the need to support and enhance planning capabilities in wildfire risk mitigation, and doing so in the context of social vulnerability. Perhaps the most critical area of focus is the wildland urban interface (WUI) given the proximity of people to fire prone landscapes, as a significant increase of fire in recent decades has been observed. The scale, frequency and intensity of fires with devastating impacts to life-safety, property and other high value assets has been substantial. Ensuring that people, property and infrastructure are safe is a major priority, but will not happen by chance. Analytical tools, risk reduction strategies and operational plans to enhance wildfire resilience, particularly in the WUI, are vital. A challenge is selecting the best areas for wildfire risk mitigation within the WUI that are contiguous and manageable in size. GeoAI and spatial optimization were demonstrated to be important tools to support planning and policy efforts. Geographic analytics in wildfire risk mitigation within the WUI of Santa Barbara highlighted the importance of spatial optimization combined with GeoAI in strategic coordination of scarce resources to enhance wildfire resilience. Computational processing of two hours was required for spatial simulation to estimate wildfire hazard mitigation benefit and spatial analytics were employed to estimate social vulnerability. These were then used to obtain mitigation traedoffs summarized in Table 3 based on the evaluation and solution of 639 problem instances (nine scenarios, with 71 different Ψ threshold values) as well as the single objective problem instances noted above (twelve in total). This puts total computational effort to carry out the reported analysis of approximately 28 days since each problem instance was limited to an hour to solve. Also, two scenarios were increased to allow 3 h of problem solution, translating to nearly 9 days of computing for each scenario. Collectively, this is a rather significant computational undertaking.

The findings highlighted the tradeoffs possible when multiple considerations are taken into account. This is the essence of identifying wildfire risk mitigation strategies that can account for the complex set of performance objectives in a community, and eventually allow for the evaluation of coexistence strategies. This also represents a first step in using GeoAI and spatial optimization to support this.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgements

The generous support of Yardi Systems through the Wildfire Resilience Initiative at University of California, Santa Barbara is gratefully acknowledged.

Appendix A

This appendix offers details on the derived attributes associated with wildfire hazard mitigation benefit and social vulnerability that are critical input for the bi-objective spatial optimization model, (1)-(7).

The FlamMap simulation executed a random fire generation within the study region, repeating this multiple times to estimate important observed characteristics. Minimum Time Travel method is employed to model each fire, yielding fire intensity values for individual cells and fire perimeters. After integrating all simulated outcomes, two variables of particular interest emerge: conditional flame length and burn probability. Conditional flame length reflects potential behavior if a given cell burns, and is an indicator of the intensity of the fire at a specific location. Burn probability represents the likelihood of a given location to be affected by fire over a specified period. Practically, it is the number of times each cell is covered within fire perimeters. The two variables can be integrated to reflect an overall fire risk. Consider the following notation:

l = index of cells (30x30 m).
λ_{li} = portion of cell l that is within parcel.i
c_l = conditional flame length in cell.l
χ_l = burn probability for cell.l
Δ_i = set of cells intersecting parcel.i

With this notation, the wildfire risk mitigation benefit is a function of both conditional flame length and burn probability:

$$\beta_i = a_i \sum_{l \in \Delta_i} \lambda_{li} f(c_l, \chi_l) \tag{10}$$

The function, *f(.)*, gives a value that corresponds to the integrated interpretation of these two observed variables as indicated in Table A1. This is a classification of relative hazard levels from 1 to 5. Each of these classes represents a discrete, relative level of potential fire hazard, where 5 represents the highest degree of hazard. Since the wildfire simulation is based on a spatial resolution of 30 x 30 m requiring 2,400,864 cells, this must be summarized at the parcel level.

The wildfire risk mitigation benefit across the region is shown in Fig. A1, highlighting the inherent spatial heterogeneity.

Social vulnerability is a consideration of great interest across a range of analysis, planning, management and policy context. The Centers for Disease Control and Prevention (2022) describes social vulnerability as being comprised of four themes reflecting the challenges faced by a community that could limit their response to a hazardous event. The first theme considers socioeconomic status, characterizing the vulnerable as those who live below 150 % of the HHS poverty line, those who are unemployed, those with a high house cost burden, those without a high school diploma, or those with no health insurance. The second theme incorporates household characteristics, with the vulnerable as those who are young (aged 17 and younger), old (aged 65 and older), households with a single parent of those that lack English proficiency. The third theme considers racial and ethnic minority status, where the vulnerable are those that belongs to minority ethnicities (e.g., Hispanic or Latino, Asian, Black, Pacific Islander or Native Hawaiian, and other minority races). The fourth theme accounts for the housing type and transportation, with the vulnerable being those living in multi-unit structures, mobile homes, group quarters, people with no vehicle, or those who living in crowded quarters.

Rather than repeat past effort that characterize social vulnerability, this research instead relies on two different products that have derived social vulnerability for the entire United States. Areal interpolation was performed by leveraging the block group and 1x1 km grid estimates of Bryan (2022) and the NASA Socioeconomic Data and Applications Center, respectively. The technical details utilize the following notation:

g = index of block groups
$\widehat{s}_g$ = social vulnerability measure for block group g $[0,1]$
$\widehat{\lambda}_{gi}$ = portion of block group g that is within parcel i
$\widehat{\Delta}_g$ = set of block groups intersecting parcel i
k = index of social vulnerability cells (1x1 km)
$\widetilde{s}_k$ = social vulnerability measure for cell k $[0,1]$
$\widetilde{\lambda}_{ki}$ = portion of cell k that is within parcel i
$\widetilde{\Delta}_k$ = set of cells intersecting parcel i

With this notation, the social vulnerability measure for the parcel is as follows:

$$\delta_i = a_i \left[\sum_{g \in \widehat{\Delta}_i} \widehat{\lambda}_{gi} \widehat{s}_g + \sum_{k \in \widetilde{\Delta}_i} \widetilde{\lambda}_{ki} \widetilde{s}_k \right] \tag{11}$$

The areal interpolation was carried out by calculating the area ratio between the parcel and each intersecting geographic unit. This area ratio was used to weight the corresponding block group and 1x1 km grid social vulnerability values. Validation of this process is summarized in Table A2, comparing the use of three different areal interpolation sources: block group only, 1 km grid only, and both. The evaluation of each case was conducted by calculating the rooted mean squared errors (RMSE) between the two ground truths: block group and 1x1 km grid. It was observed that the areal interpolation approach utilizing both sources yielded the lowest RMSEs compared to using either one of them independently. Considering intersections between 26,326 parcels, 1,981 grid cells, and 182 block groups, required processing time was approximately 2 h. The resulting social vulnerability measure at the parcel level is summarized in Fig. A2.

References

Ager, A.A., Vaillant, N.M., McMahan, A., 2013. Restoration of fire in managed forests: a model to prioritize landscapes and analyze tradeoffs. Ecosphere 4 (2), 1–19.

Ager, A.A., Evers, C.R., Day, M.A., Alcasena, F.J., Houtman, R., 2021. Planning for future fire: Scenario analysis of an accelerated fuel reduction plan for the western United States. Landsc. Urban Plan. 215, 104212.

Bakkensen, L.A., Fox-Lent, C., Read, L.K., Linkov, I., 2017. Validating resilience and vulnerability indices in the context of natural disasters. Risk Anal. 37 (5), 982–1004.

Blier, W., 1998. The sundowner winds of Santa Barbara, California. Weather Forecast. 13 (3), 702–716.

Bryan, M., 2022. US Social Vulnerability by Census Block Groups (https://doi.org/10.7910/DVN/ARBHPK, accessed 5/30/23).

Calkin, D. E., Cohen, J. D., Finney, M. A., Thompson, M. P., 2013. How risk management can prevent future wildfire disasters in the wildland-urban interface. https://doi.org/10.1073/pnas.1315088111.

Cao, K., 2017. Spatial optimization for sustainable land use planning. In: Huang, B. (Ed.), Comprehensive Geographic Information Systems. (Elsevier), pp. 244–252.

Carvalho, L., Duine, G.J., Jones, C., Zigner, K., Clements, C., Kane, H., Gore, C., Bell, G., Gamelin, B., Gomberg, D., Enos, W., 2020. The sundowner winds experiment (SWEX) pilot study: Understanding downslope windstorms in the Santa Ynez Mountains, Santa Barbara, California. Monthly Weather Rev. 148 (4), 1519–1539.

Centers for Disease Control and Prevention. (2022). Social Vulnerability Index (https://www.atsdr.cdc.gov/placeandhealth/svi/documentation/pdf/SVI2020Documentation_08.05.22.pdf, accessed 5/30/23).
Chung, W., Jones, G., Krueger, K., Bramel, J., Contreras, M., 2013. Optimising fuel treatments over time and space. Int. J. Wildland Fire 22 (8), 1118–1133.
Church, R.L., 2001. Spatial optimization models. In: Smelser, N., Baltes, P. (Eds.), International Encyclopedia of the Social & Behavioral Sciences. (Elsevier), pp. 14811–14818.
Cohon, J.L., 1978. Multiobjective Programming and Planning. Academic Press.
County of Santa Barbara (2023). Land use designation and zoning map (https://www.countyofsb.org/3182/16603/LAND-USE-DESIGNATION-AND-ZONING-MAP, accessed 6/2/23).
Finney, M.A., 2002. Fire growth using minimum travel time methods. Can. J. For. Res. 32 (8), 1420–1424.
Hof, J.G., Bevers, M., 1998. Spatial optimization for managed ecosystems. Columbia University Press.
Jones, C., Carvalho, L.M., Duine, G.J., Zigner, K., 2021. Climatology of Sundowner winds in coastal Santa Barbara, California, based on 30 yr high resolution WRF downscaling. Atmos. Res. 249, 105305.
Kent, B., Bare, B.B., Field, R.C., Bradley, G.A., 1991. Natural resource land management planning using large-scale linear programs: the USDA Forest Service experience with FORPLAN. Oper. Res. 39 (1), 13–27.
Kim, Y.H., Bettinger, P., Finney, M., 2009. Spatial optimization of the pattern of fuel management activities and subsequent effects on simulated wildfires. Eur. J. Oper. Res. 197 (1), 253–265.
Li, W., 2020. GeoAI: Where machine learning and big data converge in GIScience. J. Spat. Inform. Sci. 20, 71–77.
Longley, P.A., Goodchild, M.F., Maguire, D.J., Rhind, D.W., 2015. Geographic information systems and science, 4th edition. John Wiley & Sons.
Manzello, S.L., Blanchi, R., Gollner, M.J., Gorham, D., McAllister, S., Pastor, E., Planas, E., Reszka, P., Suzuki, S., 2018. Summary of workshop large outdoor fires and the built environment. Fire Saf. J. 100, 76–92.
Moritz, M.A., Batllori, E., Bradstock, R.A., Gill, A.M., Handmer, J., Hessburg, P.F., Leonard, J., McCaffrey, S., Odion, D.C., Schoennagel, T., Syphard, A.D., 2014. Learning to coexist with wildfire. Nature 515 (7525), 58–66.
Murray, A.T., 2010. Quantitative geography. J. Reg. Sci. 50 (1), 143–163.
Murray, A.T., 2021. Significance assessment in the application of spatial analytics. Ann. Am. Assoc. Geogr. 111 (6), 1740–1755.
Murray, A.T., Church, R.L., Pludow, B.A., Stine, P., 2022. Advancing contiguous environmental land allocation analysis, planning and modeling. J. Land Use Sci. 17 (1), 572–590.
Murray, A.T., Church, R.L., 2023. Spatial optimization of multiple area land acquisition. Comput. Oper. Res. 106160.
Murray, A.T., Carvalho, L., Church, R.L., Jones, C., Roberts, D., Xu, J., Zigner, K., Nash, D., 2021. Coastal vulnerability under extreme weather. Appl. Spat. Anal. Policy 14, 497–523.
Onal, H., Wang, Y., Dissanayake, S.T., Westervelt, J.D., 2016. Optimal design of compact and functionally contiguous conservation management areas. Eur. J. Oper. Res. 251 (3), 957–968.
O'Sullivan, D., Unwin, D., 2010. Geographic information analysis, 2nd edit. John Wiley & Sons.
Pludow, B.A., Murray, A.T., 2023. Accounting for spatial spillover benefits in neighborhood wildfire risk mitigation. Landsc. Urban Plan. 233, 104684.
Pludow, B.A., Murray, A.T., Echeverri, V., Church, R.L., 2023. Evaluation of forest treatment planning considering multiple objectives. J. Environ. Manage. 346, 118997.
Radeloff, V.C., Helmers, D.P., Kramer, H.A., Mockrin, M.H., Alexandre, P.M., Bar-Massada, A., Butsic, V., Hawbaker, T.J., Martinuzzi, S., Syphard, A.D., Stewart, S.I., 2018. Rapid growth of the US wildland-urban interface raises wildfire risk. Proc. Natl. Acad. Sci. 115 (13), 3314–3319.
Rogerson, P.A., 2020. Statistical methods for geography, 5th edit. Sage, Thousand Oaks, CA.
Schoennagel, T., Balch, J.K., Brenkert-Smith, H., Dennison, P.E., Harvey, B.J., Krawchuk, M.A., Mietkiewicz, N., Morgan, P., Moritz, M.A., Rasker, R., Whitlock, C., 2017. Adapt to more wildfire in western North American forests as climate changes. Proc. Natl. Acad. Sci. 114 (18), 4582–4590.
Scott, J.H., Burgan, R.E., 2005. Standard fire behavior fuel models: A comprehensive set for use with Rothermel's surface fire spread model (General Technical Report RMRS-GTR-153). USDA Forest Service, Rocky Mountain Research Station, Fort Collins CO.
Shirabe, T., 2005. A model of contiguity for spatial unit allocation. Geogr. Anal. 37 (1), 2–16.
Smith, T.R., 1984. Artificial intelligence and its applicability to geographical problem solving. Professional Geographer 36 (2), 147–158.
Spielman, S.E., Tuccillo, J., Folch, D.C., Schweikert, A., Davies, R., Wood, N., Tate, E., 2020. Evaluating social vulnerability indicators: criteria and their application to the Social Vulnerability Index. Nat. Hazards 100, 417–436.
Tong, D., Murray, A.T., 2012. Spatial optimization in geography. Ann. Assoc. Am. Geogr. 102 (6), 1290–1309.
US Census Bureau (2021). American Community Survey Data (https://www.census.gov/programs-surveys/acs/data.html, accessed 6/2/23).
US Department of Interior Interagency Fuel Treatment Decision Support System (https://iftdss.firenet.gov/landing_page/ 2023 accessed 5/30/23.
Wei, Y., Rideout, D., Kirsch, A., 2008. An optimization model for locating fuel treatments across a landscape to reduce expected fire losses. Can. J. For. Res. 38 (4), 868–877.
Wigtil, G., Hammer, R.B., Kline, J.D., Mockrin, M.H., Stewart, S.I., Roper, D., Radeloff, V. C., 2016. Places where wildfire potential and social vulnerability coincide in the coterminous United States. Int. J. Wildland Fire 25 (8), 896–908.
Williams, J.C., 2002. A zero-one programming model for contiguous land acquisition. Geogr. Anal. 34 (4), 330–349.
Wisner, B., Blaikie, P., Cannon, T., Davis, I., 2004. At Risk: Natural Hazards, People's Vulnerability, and Disasters, 2d ed. Routledge, London.
Wright, J., ReVelle, C., Cohon, J., 1983. A multiobjective integer programming model for the land acquisition problem. Reg. Sci. Urban Econ. 13 (1), 31–53.
Xiao, N., Murray, A.T., 2019. Spatial optimization for land acquisition problems: A review of models, solution methods, and GIS support. Trans. GIS 23 (4), 645–671.
Yao, J., Zhang, X., Murray, A.T., 2018. Spatial optimization for land-use allocation: accounting for sustainability concerns. Int. Reg. Sci. Rev. 41 (6), 579–600.
Zigner, K., Carvalho, L.M., Jones, C., Benoit, J., Duine, G.J., Roberts, D., Fujioka, F., Moritz, M., Elmquist, N., Hazard, R., 2022. Wildfire risk in the complex terrain of the Santa Barbara wildland–urban interface during extreme winds. Fire 5 (5), 138.