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Research paper

Can private land conservation reduce wildfire risk to homes? A case study in San Diego County, California, USA

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HIGHLIGHTS

- Private land conservation can help to mitigate fire risk.
- The impact is maximized if high fire areas are targeted.
- Impacts are heterogeneous at the municipal scale.

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ABSTRACT

The purchase of private land for conservation purposes is a common way to prevent the exploitation of sensitive ecological areas. However, private land conservation can also provide other benefits, one of these being natural hazard reduction. Here, we investigated the impacts of private land conservation on fire risk to homes in San Diego County, California. We coupled an econometric land use change model with a model that estimates the probability of house loss due to fire in order to compare fire risk at the county and municipality scale under alternative private land purchasing schemes and over a 20 year time horizon. We found that conservation purchases could reduce fire risk on this landscape, and the amount of risk reduction was related to the targeting approach used to choose which parcels were conserved. Conservation land purchases that targeted parcels designated as high fire hazard resulted in lower fire risk to homes than purchases that targeted low costs or high likelihood to subdivide. This result was driven by (1) preventing home placement in fire prone areas and (2) taking land off the market, and hence increasing development densities in other areas. These results raise the possibility that resource conservation and fire hazard reduction may benefit from combining efforts. With adequate planning, future conservation purchases could have synergistic effects beyond just protecting ecologically sensitive areas.
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1. Introduction

The purchase of private land for conservation purposes is one of the most common means of protecting sensitive ecological resources and preserving open space worldwide (Davies, Kareiva, & Armsworth, 2010; Fishburn, Kareiva, Gaston, & Armsworth, 2009). The massive land holdings (fee title and easements) of national and local land trusts now cover more than 20 million ha in the United States alone (Land Trust Alliance, 2011). Most often, private land conservation is justified as a means to preserve biodiversity, scenic beauty, or open space (Merenlender, Huntsinger, Guthey, & Fairfax, 2004; Rissman & Merenlender, 2008; Wallace, Theobald, Ernst, & King, 2008).

Beyond biodiversity protection and scenic values, open spaces provide additional benefits. For example, increased property values (Fausold & Lilieholm, 1999; Geoghegan, 2002), economic growth (Lewis, Hunt, & Plantinga, 2002), and the provision of ecosystem services (Goldman & Tallis, 2009) have all been correlated with the presence of conserved lands in a community. In addition, conserved lands can reduce the human impact of natural hazards such

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as floods, hurricanes, and potentially wildfires (Bihari, Hamin, & Ryan, 2012; Daniels, 2005; Schmidt, Moore, & Alber, 2014; Tang, 2008). While these benefits are acknowledged by scientists and practitioners alike, the potential benefit of hazard reduction is less commonly used to drive private land conservation decision-making in the selection of where conservation takes place.

Traditional motivations for land conservation and the need for hazard reduction meet head on in the wildland urban interface (WUI), where houses are adjacent to or interspersed with wildland vegetation (Radeloff et al., 2005). In many fire-prone regions with large numbers of human-caused ignitions, medium housing densities common in the WUI have the highest fire risk (Syphard et al., 2007; Syphard, Keeley, Bar Massada, Brennan, & Radeloff, 2012). These areas provide a unique combination of people to start fires, fuels to burn, and limited firefighting accessibility that lead to high fire risk to homes (Bar Massada, Radeloff, Stewart, & Hawbaker, 2009; Whitman, Rapaport, & Sherren, 2013). This type of housing development- commonly referred to as sprawl-is also one of fastest growing in the United States (Lubowski, Plantinga, & Stavins, 2008; Newburn & Berck, 2011), and many organizations involved in private land conservation attempt to limit it (Brewer, 2004).

The dynamic of active land conservation, high fire risk, and developing landscapes indicate the potential for private land conservation to jointly impact urban sprawl and fire risk in the WUI. The linkages between private land conservation and fire risk reduction, however, are likely to be complex due to land market dynamics (Armsworth, Daily, Kareiva, & Sanchirico, 2006) and the complex spatial determinates of fire risk (Bowman, O'Brien, & Goldammer, 2013; Hardy, 2005). The location of fire risk may be changed if private land conservation displaces development from one area to another area (Lewis, Provencher, & Butsic, 2009) or if it increases housing density in current developments. Likewise, if displaced development moves to areas of higher fire hazard, private land conservation could even increase fire risk. Private land conservation could also change the spatial arrangement and density of housing by limiting areas where housing can be built, and this has been shown to impact fire risk as well (Syphard, Bar Massada, Butsic, & Keeley, 2013). This can impact the fire risk of both new and existing houses. Therefore, for private land conservation to be a useful tool in reducing fire risk, we must understand the dynamics between conserving land, development patterns, and the drivers of fire risk.

We address the potential congruencies between private land conservation and fire risk reduction in San Diego County CA, USA, a fast-growing and fire-prone region, where private land conservation plays an important role in land use planning and natural resource protection (Land Trust Alliance, 2015). We combine the dynamics of housing growth, private land conservation and fire risk to empirically estimate the impact of private land conservation on fire risk to current and new homes. We accomplish this by simulating land development, conservation purchases and fire risk to houses over a 20 year time horizon given a fixed conservation budget and constant rate of housing growth. Further, we integrate multiple site selection algorithms into our simulation technique in order to identify which features (monetary costs, likelihood of development, or wildfire hazard) are most important when selecting parcels to conserve in a way that reduces fire risk in the most cost-effective manner. Our approach addresses three research questions:

At the county scale, can private land conservation be used to reduce fire risk to homes over a 20 year time horizon?

What are the impacts of the county-level conservation program on municipal-level fire risk?

What private land conservation selection strategies reduce fire risk to homes the most, given a budget constraints?

2. Methods

2.1. Study area

Our study area was the South Coast ecoregion of San Diego County, which covers about 80% of the county (Fig. 1). San Diego County is characterized by a Mediterranean climate, which results in hot dry weather during late spring, summer and early autumn. Every autumn, when fuels are driest, Santa Ana wind events, lasting several days and gusting over 110 km/h, with low humidity create extreme fire weather conditions. Fires that occur during these wind events spread rapidly and have resulted in massive areas burned both historically and recently. In the last decade, Santa Ana wind-driven fires have been responsible for the destruction of thousands of homes in San Diego (Keeley, Fotheringham, & Moritz, 2004; Keeley, Safford, Fotheringham, Franklin, & Moritz, 2009). San Diego also boasts a large and expanding WUI (San Diego County, 2011; Syphard, Clarke, Franklin, Regan, & McGinnis, 2011). Although some parts of the county fall squarely into undeveloped or densely developed areas, many of the more recently developed areas are at low to medium housing densities (Hammer, Radeloff, Fried, & Stewart, 2007).

To help preserve its native ecosystems (San Diego County has the most endemic plants and threatened and endangered species of any county in the continental U.S. (Regan et al., 2008)), San Diego County has been purchasing private land for conservation since the 1990s. Private land conservation references the purchase of land for conservation purposes, by private actors. Typically in San Diego County this work is done by Land Trusts, which are not for profit groups who specialize in holding land. There are at least 14 member organizations of the Land Trust Alliance who are actively protecting land in the County (Land Trust Alliance, 2015). Under the Multi Species Conservation Program, local governments have a goal of protecting 172,000 acres, much of it through land purchases (San Diego County, 2015). In many cases, government grants are available to land trusts in San Diego County to provide funds for conservation purchases.

2.1.1. Simulating future growth, private land conservation, and fire risk

To understand the impact of private land conservation on fire risk, we use a coupled simulation framework where models of land development, selection algorithms that choose what parcels should be conserved, and models that predict fire risk are combined. We use this combined modeling framework to simulate land development, land conservation and fire risk, over a 20 year time horizon, in five year increments. We address each component model in turn and discuss their integration.

2.2. Land development model

To determine the likelihood that a given parcel will develop over the 20 year time horizon of our study, we developed an econometric model of parcel subdivision using parcel data over three time periods: 2004, 2010, and 2014. We parameterized our model using a random effects probit model where the dependent variable is binary (1 if a subdivision occurs, 0 otherwise) (Wooldridge, 2011). We included independent variables that have been shown to impact land owner decisions to subdivide in similar settings (Carrion-Flores & Irwin, 2010; Irwin et al., 2009; Syphard et al., 2013). These variables included: lot size, a number of dummy variables to account for non-linear impacts of lot size, zoning type, municipality identification variables, elevation and slope of parcel, as well as distance from the ocean, the nearest sewer line, freeways, public park, floodplain, and nearest lake. All data came from San Diego Association of Governments (SANDAG, www.sandag.org).

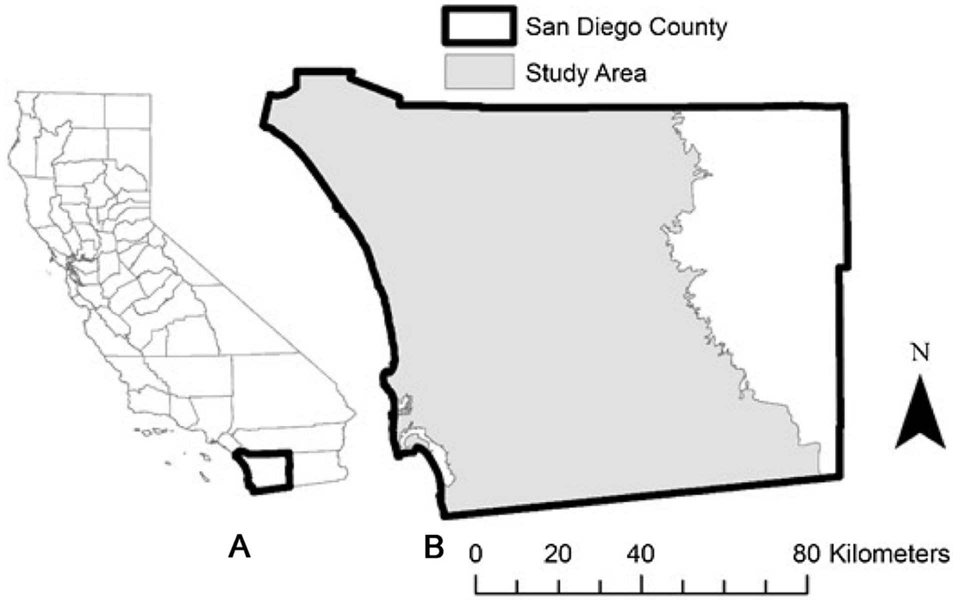

Fig. 1. (A) State of California. (B) San Diego County, and study area.

Only parcels that were considered developable (i.e., they were large enough to subdivide under current zoning laws, and were also considered to have development potential by the San Diego County General Plan), were used in the regressions (San Diego County, 2011). Overall, the model had a pseudo R squared of 0.295, a high goodness of fit for this type of model. We then used the regression output to predict the probability of each parcel subdividing in each 5 year period. Full regression results are available in the SI.

2.3. Private land conservation selection model

We tested four selection strategies r to find the most cost effective way to reduce fire risk to houses using private land conservation. In our setting, we had multiple dynamics that made choosing which parcels to select in each time period a difficult decision. The impact of selecting a parcel for conservation was based on: (1) how likely that parcel was to subdivide (T); (2) how much it costs (C); and (3) the fire hazard associated with it (F). For smaller problems, stochastic dynamic programming can find a truly optimal selection pattern (Butsic, Lewis, & Radeloff, 2013; Costello and Polasky, 2004). However, for large problems like this one, true optimization is not possible and hence we relied on heuristic algorithms that ranked parcels for conservation based on their characteristics. Similar algorithms have been effective in other settings (Newburn, Reed, Berck, & Merenlender, 2005; Newburn, Berck, & Merenlender, 2006).

In total we ran four selection algorithms. The first, Cost Minimization (CostMin), simply selected the parcels with the least cost per hectare (C/ha low to high values). This algorithm will protect the most land. Cost per hectare was derived from county assessment data (www.sandag.org). The second, SubMax, selected the parcels that were most likely to subdivide (T, sorted high to low), preventing areas that would have subdivided in the absence of protection from developing. The likelihood of subdivision was calculated from the random effects probit model described previously.

The third strategy, Fire Minimization (FireMin), weighted the CostMin strategy by the average fire hazard of each parcel, such that parcels that were designated as most hazardous received a higher weight ((C/ha)/F low to high). This ranking will protect large parcels that are likely to burn. Fire hazard rankings were derived from maps developed by the California Department of Forestry and Fire Protection (http://www.fire.ca.gov/) and customized for San Diego County (http://www.sandiego.gov/fire/pdf/fhszfaq.pdf). Fire Hazard was calculated using five variables: vegetation density, slope severity, five minute fire department response time, road proximity, and proximity to fire hydrants. Maps were created in 2006–2007, so some changes in components of the rankings may have changed over time. While we think most of these changes would minimally impact the rankings – for instance it seems unlikely that fire response time would change greatly in the interim – if they did, the exact locations of purchases may change on the landscape, but we might expect the same general dynamics within the system. The fourth strategy, FireMinMax, further weighted the FireMin strategy by the likelihood a parcel would subdivide, giving parcels that were more likely to subdivide more weight ((C/ha)/F)/T) (Table 1).

2.4. Fire risk to housing model

Fire risk to housing was calculated based on a model that related housing loss in the previous decade to a suite of explanatory variables, including housing density (Table 2). We focused on landscape-scale factors that contribute to the likelihood of structure loss through the exposure of the structure to fires, either via spreading flames or fire brands. We did not account for local-scale factors such as building construction and defensible space that would be important for structure survival given the exposure (Gibbons et al., 2012). To project fire risk to structures under different conservation selection algorithms, we used MaxEnt (Elith et al., 2011; Phillips, Anderson, & Schapire, 2006), a map-based program that runs a machine-learning algorithm to iteratively evaluate contrasts among values of a mapped dependent variable (here, a structure destroyed by wildfire) with a range of mapped environmental predictor variables sampled across the landscape. Here we used the same model and variables that were used in Syphard et al. (Syphard et al., 2013; Syphard, Keeley, Massada, Brennan, & Radeloff, 2012) The dependent variable was the location of structures that were destroyed by fire during the period 2001 and 2010, and the explanatory variables included maps delineating housing location and pattern, including structure density and proximity to

Table 1
Four selection algorithms for selecting which parcel to conserve. C is equal to the cost of conservation. ha is equal to the size of the parcel, T is equal to the likelihood of transition of land use of the parcel and F is equal to the fire hazard of the parcel.

	Formula	Ranking	Intuition
CostMin	*C/ha*	Low to high	Acquire as much property as possible at the least cost
SubMax	*T*	High to low	Acquire parcels that will develop in the absence of conservation
FireMin	*(C/ha)/F*	Low to high	Acquire inexpensive parcels that are at high fire risk
FireMinMax	*((C/ha)/F)/T*	Low to high	Acquire parcels that are inexpensive, likely to subdivide, and at high risk of fire

other structures and roads, as well as structure location within groups of structures (i.e., housing clusters) to estimate proximity to settlement edge and interspersion with wildland vegetation. Other variables included biophysical factors such as fuel type and terrain. The modeled output was an exponential function that delineated the probability of a structure being destroyed by fire across an entire gridded map. This probability reflected both the likelihood of a large fire and the likelihood of structure destruction because the location of destroyed structures reflected both of these conditions relative to the rest of the landscape that was used for background data.

We ran the MaxEnt model using 10 000 random background points, separating the data into 80% training and 20% testing, and replicated the runs five times using cross-validation. Based on Elith et al. (2011) and Syphard et al. (2012a, 2012b, 2013), we increased the regularization setting to 2.5 and used only hinge, linear, and quadratic functions to estimate the model to minimize over-fitting of the model. In the simulation, the fire risk probabilities were updated to account for new structures on the landscape over time. In our model, fire risk is dynamic because it changes over time as new structures are added to the landscape. However, we did not model vegetation changes, as these would add an unnecessary level of uncertainty to our analysis and potentially confound interpretation of results. Fine-scale processes like post-fire succession and fuel conditions are highly stochastic and uncertain; and broader-scale changes, such as those in fuel type, would unlikely be substantial within the 30-year window of our simulation.

2.5. Models and simulations

We coupled the models using the following steps.

1. Starting with the actual parcel data from 2014, we used the econometric model to estimate the transition probability of each "developable" parcel on the landscape.
2. We then used the county assessment of each property to calculate the cost of purchasing each parcel.
3. Next, using one of the four selection algorithms, parcels were selected for conservation until the budget was used up. If funds were left over, they carried over to the next time period.
4. A five-year time step was simulated. As parcels subdivided based on their transition probability, new houses were added to the landscape at a housing density based on current zoning regulations. We assumed that parcels subdivide at their maximum density allowed by zoning. Parcels subdivided and new homes were added until 37,500 new homes were developed in that time period.
5. Steps 3–4 repeat until the end of the simulation in 2034.

The MaxEnt fire risk model was applied to the simulated landscape, and fire risk was calculated for all of the existing and new simulated structures across the county as a whole as well as for each municipality. To operationalize our simulations, we made a number of assumptions. First, we assumed that 37,500 houses are added to the landscape in each five year period. This assumption was based on estimates of housing growth to 2030 by SANDAG, the regional planning agency. Therefore, when a conservation purchase was made in our simulation, it did not reduce the total number of houses on the landscape. Rather, it simply prevented houses from being built on the land that was purchased. Given the limited budget available to private land conservation, it seems unlikely that purchasing land would limit the number of houses at the county scale. Likewise, we did not expect private land conservation to influence housing demand at the county level.

Second, we assumed that the subdivision probabilities were stationary throughout the simulation. We made this assumption to simplify our simulation framework and because updating the subdivision probabilities in each time period would require us to interpret the coefficients of the econometric model as causal. Given the problems of endogenous variables in models of land use change (Carrion-Flores & Irwin, 2010; Irwin & Bockstael, 2004; Towe, Nickerson, & Bockstael, 2008), and the lack of causal structure in our data, we were more confident interpreting the results of our econometric model as predictions of development, rather than the impact of individual coefficients to this development.

We also simulated our scenarios under two different budgets. The baseline budget was $200,000.000 per five years ($40,000.000 per year), and we ran our simulation at this level as well as at $400,000.000 to avoid issues of inflation, we assumed that the conservation budget increases with property prices (Fig. 2).

3. Results

At the county scale we found that the impact of private land conservation on fire risk to homes depended critically on the algorithm used to select parcels for conservation. At the end of the 20 year simulation, the CostMin algorithm increased the likelihood that a home would burn by 1.24% relative to a baseline simulation with no private land conservation. The SubMax, algorithm increased the likelihood that a home would burn by 13.57% relative to the baseline. The algorithms that included fire as a selection criteria fared much better. The FireMin algorithm decreased fire risk to structures by 12.56%, while the FireMinMax algorithm decreased fire risk to structures by 12.74% at the end of the simulation (Fig. 3).

Looking at fire risk at each 5 year time step, the results diverged over time. After the first time step, average fire risk per home at the county scale was between a high 0.024% for the SubMax algorithm and a low of 0.022% for the FireMax and FireMinMax algorithm, respectively. By the end of the simulation, however, average fire

Table 2
Explanatory variables and their relative contributions to the MaxEnt model used to predict fire risk.

Variable	Percent contribution	Relationship to structure destruction
Housing density	35.6	Negative
Size of housing cluster	30	Negative
Fuel type	20.6	NA
Distance to coast	11.2	Intermediate
Historical fire frequency	1.7	Intermediate
Percent slope	0.7	Positive
Distance to edge of housing cluster	0.2	Negative
Southwestness (transformed aspect)	0.1	NA

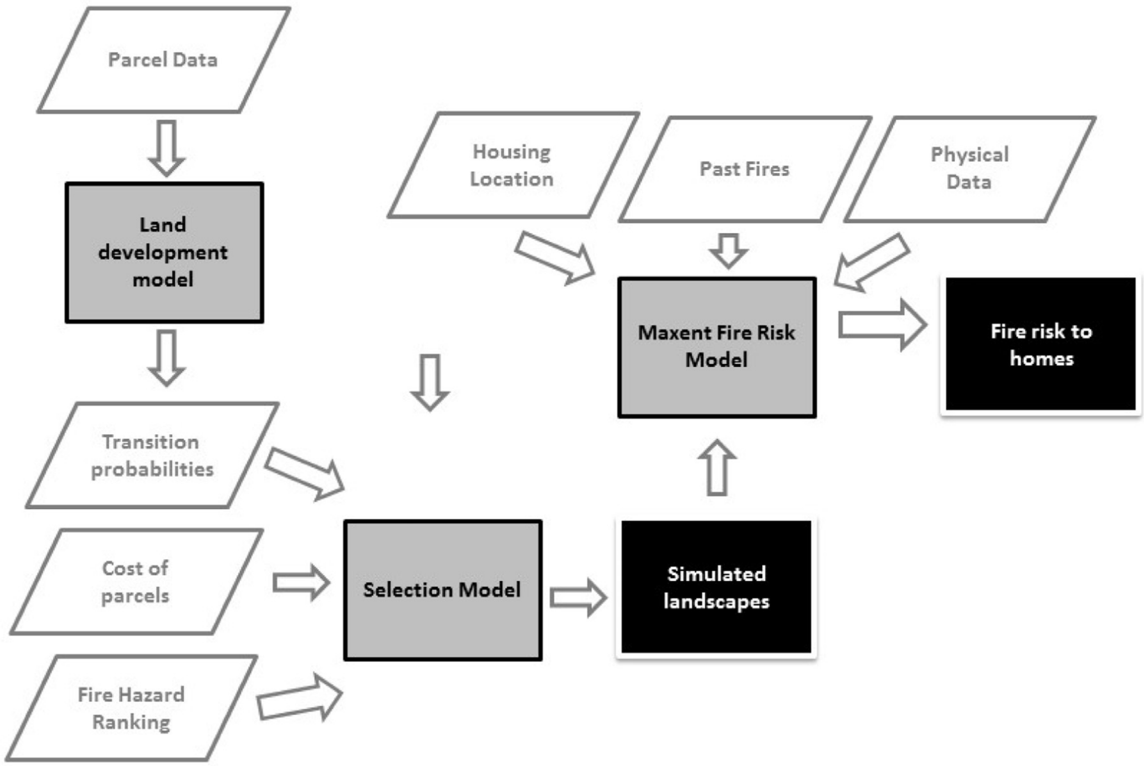

Fig. 2. Workflow for models. Unshaded boxes represent data inputs. Grey boxes represent models. Black boxes represent outcomes.

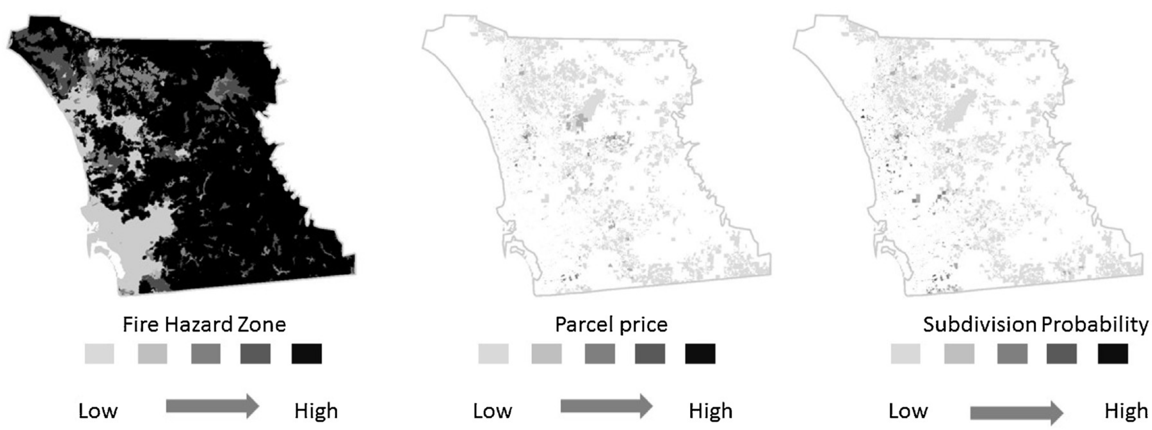

Fig. 3. Fire Hazard Zones, Parcel Price, and Subdivision Probability for the study area.

risk was nearly 30% higher for the average home under the SubMax algorithm compared to the FireMinMax algorithm (Fig. 4).

The spatial pattern of fire risk was similar under each algorithm and the baseline – with less fire risk along the coast and fire risk peaking in the WUI prone central area of the county. However, the impact of the selection algorithms on land development and subsequent fire risk was twofold. First, the direct impact of integrating fire into the selection algorithm led to purchases of more fire-prone parcels. This directly prevented parcels with high fire potential from being developed. Second, purchasing fire-prone parcels tended to leave less room for development in the more rural, fire-prone eastern part of the county. Thus, the fire algorithms forced development into denser and more clustered arrangements, in less fire-prone areas in the east. This resulted lowered projected fire risk, particularly in areas of medium development density (Fig. 5).

Looking at the impacts of the county level program on individual communities, we see very heterogeneous results. Some municipalities ended up with higher fire risk, even when the FireMaxMin algorithm was used. Out of the 17 municipalities in our dataset, 5 had higher average fire risk to homes under the selection algorithms that take fire into account. Likewise, some of these communities fared better under algorithms that otherwise increased fire risk at the county scale (Fig. 6).

Doubling the budget did decrease the fire risk when using the selection algorithms that integrate fire hazard, but additional money further increased fire risk relative to the baseline in the other scenarios. Nevertheless, the impact of increasing the conservation budget was small, particularly relative to the selection algorithm used. Indeed, the mean housing risk under the double budget scenario was identical to the 7th decimal place between the normal and double budget scenarios (Fig. 3).

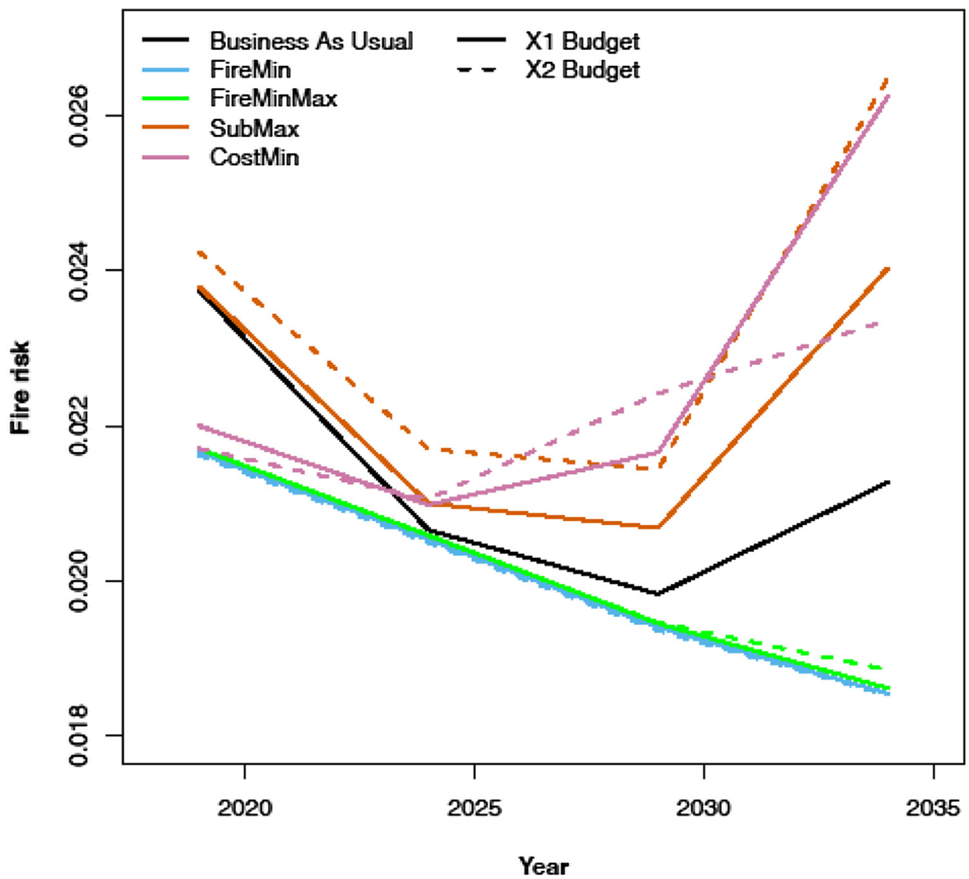

Fig. 4. Fire risk to homes in each time period, for each selection algorithm and for each budget.

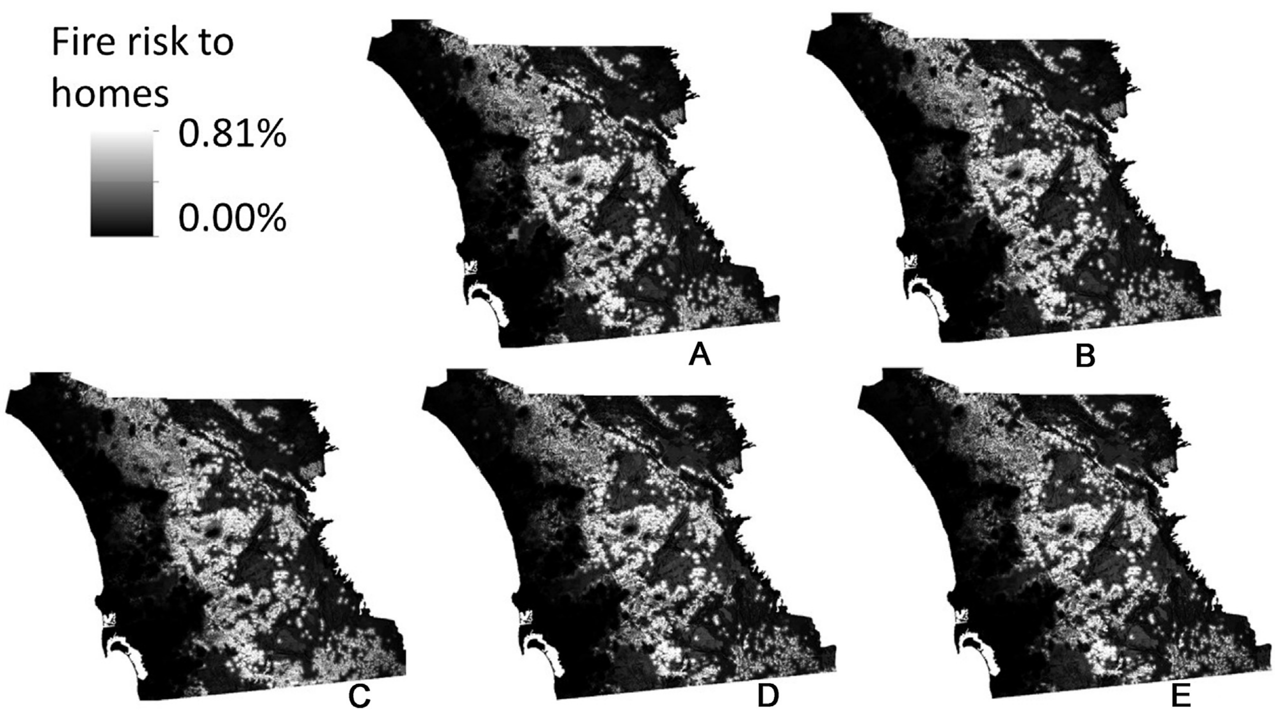

Fig. 5. Fire risk to homes for San Diego County in 2034. Map A is the baseline simulation where no conservation purchases take place. Map B is the result of the CostMin Algorithm. Map C. is the SubMax algorithm. Map D is the FireMin algorithm and Map E is the FireMinMax algorithm. Key areas for different outcomes are the central areas of the maps, as well as the south east corner of the map. In these places fire risk moves under alternative selection algorithms.

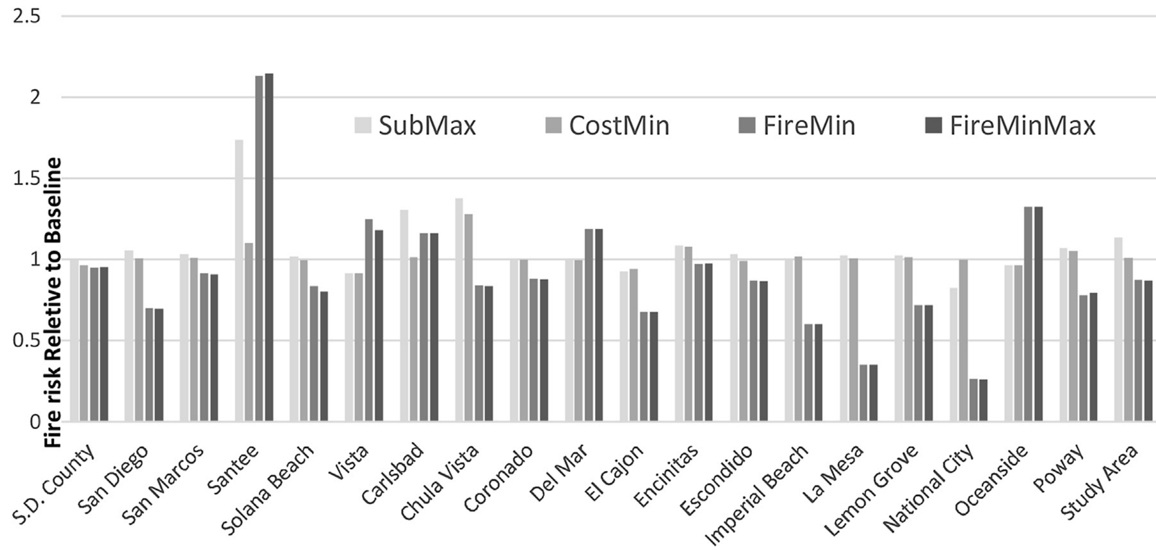

Fig. 6. Relative fire risk at the municipal and study area level. A value of one indicates that risk to homes is equal to the baseline simulations. Values greater than one indicate higher fire risk compared to the baseline. Values lower than one indicate lower fire risk compared to the baseline. We note that while for San Diego County as a whole mean fire risk to homes decreases for each selection algorithm, for individual municipalities there is large variation in the impact of each selection algorithm.

4. Discussion

Integrating private land conservation decision-making with wildfire risk reduction is potentially a new and innovative approach to more cost effective conservation planning. This approach may be particularly useful in Southern California where urban sprawl both increases fire risk and reduces open space. Here, we addressed whether private land conservation could be used to reduce fire risk to homes at both the county and municipal scale and how to best select parcels for conservation that reduce fire risk to homes (Fig. 5).

Our models suggest that in this region, private land conservation may reduce the fire risk to homes, but only if fire hazard was taken into account when selecting parcels. On the other hand, strategies that focused on conserving the most land or the most threatened land actually led to higher rates of fire risk to homes. In our study area, those parcels that are most likely to subdivide or that are cheapest tend to be located in areas with lower fire hazard; thus, purchasing land in those areas redirects new development into higher fire-hazard areas, where the patterns and locations of the newer structures put them at a higher risk. The most threatened and cheapest parcels were also located in areas where the patterns and arrangement of existing development offered the potential to buffer structure exposure to wildfire. That is, development that would have otherwise occurred as infill or expansion (Syphard et al., 2013) was instead displaced to less-developed areas, and in patterns that increase exposure to wildland fires. Thus, at least in this region, fire hazard and existing development patterns should both be accounted for when planning for land conservation in fire-prone areas.

Despite these county-wide trends, we found high spatial heterogeneity in the impact of private land conservation on fire risk. Interestingly, even when policies decreased fire risk on average across the county, fire risk still increased in some communities. The reason for this seemingly counterintuitive result is partly due to the fact that, in our model, housing growth continues in the county even in the presence of private land conservation. Therefore, despite the larger trend of fire risk reduction, some communities may nevertheless experience housing growth in patterns or locations that increase their fire risk. This result suggests that private land conservation alone, particularly when implemented at the county or regional level, will not be able to reduce fire risk everywhere. Indeed, it may be most effective when coupled with other land use regulations and plans that minimize fire risk for areas that develop. For example, planning policies that encourage the type of residential patterns known to reduce housing exposure to wildfire (Syphard et al., 2013) could be coupled with conservation planning efforts. These results indicate that county level policies can impact local municipalities differently, and that these results may be hard to tease out without modeling.

From a modeling perspective, our approach shows the advantages of coupling models. By using an econometric land use model in tandem with a fire risk model, we were able to identify the impacts of land conservation on fire risk as well as the impacts of different selection algorithms. Future extensions of our work would include dynamic interactions between the subdivision model and fire risk as well as potentially causal estimates of land conservation's impact on property prices and transition probabilities (Fig. 6).

An interesting extension of our model would be to focus more heavily on spatial dependencies in fire spread and conservation. Currently, our selection algorithm is not concerned with landscape features such as corridors or large patch sizes. Interestingly, focus on preserving such features may have unintended consequences for fire risk, especially if corridors may lead to fire spread. Indeed, it may be the case that preserving landscape features such as corridors may adversely impact fire risk, perhaps even at the landscape scale. Vegetation connectivity, but not vegetation type, has been shown to influence the likelihood of building loss in wildfires for some communities at a landscape scale (Alexandre et al., 2015).

Similarly, in our model we assume that conserved open space has similar risk of fire and influences fire risk on adjacent homes in the same way as unprotected open space. Whether this is actually the case will depend largely on the spatial configuration of the open space (Alexandre et al., 2015) and its relative probability of ignition, which may depend on human access (Syphard & Keeley, 2015) Aside from active fire suppression, mechanical fuel treatments designed to protect communities from fire spread are the primary fire management approach used in the region. In non-forested ecosystems like southern California, these fuel treatments have clear negative ecological impacts, and they also have limited effectiveness in controlling large fires during severe weather conditions when most homes are lost; instead, they are best used for firefighter access (Syphard, Keeley, & Brennan, 2011b; Syphard, Keeley, & Brennan, 2011c). Thus, to the extent that conserved and unprotected lands would be managed differently for fire, it is likely that the main effect would be ecological.

A final caveat of our results is that preserved open space, may or may not have conservation benefits. Here we focus exclusively on optimizing fire risk reduction. Whether or not properties which reduce fire risk reduction also have conservation benefits is unknown. If other conservation benefits, such as biodiversity or habitat for rare species occur on properties with high fire risk, it may be the case that strategies to reduce fire risk may also be good for conservation. Of course, the opposite may be true as well, and fire risk may be highest in areas with lower conservation values. It is also possible that this spatial relationship is not completely constant, and some areas may have high values of both, while others high value for one or another. Future models using multi-criteria optimization could address this problem by including measures of conservation benefits in the objective function.

With limited land conservation and hazard reduction funding available, the potential exists for conservation organizations and government agencies to use land conservation as a tool to manage biodiversity, open space, and fire concurrently. Although we are unaware of it currently being discussed in policy circles, we could imagine a future in which fire hazard dollars are best allocated to acquisition of certain lands. This combining of forces between fire and conservation goals would be a novel approach and could lead to efficiencies in both conservation and hazard reduction.

5. Conclusion

Hazard reduction is not typically a main driver of land conservation. We show here, however, that land conservation may be a useful tool in reducing risk from fire in San Diego County, California. When conservation purchases are focused on lands with high fire hazard, low costs, and high probabilities of subdivision, fire risk can be diminished at the county scale. At the municipality scale, however, the impacts are more heterogeneous, with a few municipalities actually seeing increased fire risk over the baseline simulation. Overall, our results suggest that private land conservation may have broader applications than just as a way to preserve open space.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.landurbplan.2016.05.002.

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