Tuolumne County
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Heather Ryan
Board Clerk of the
Board Of Supervisors

BOARD OF SUPERVISORS
COUNTY OF TUOLUMNE

David Goldemberg, *First District*
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Ryan Campbell, *Second District*
Daniel Anaiah Kirk, *Third District*
Jaron E. Brandon, *Fifth District*

April 4, 2023

Office of the State Fire Marshal
C/O: FHSZ Comments
California Department of Forestry and Fire Protection
P.O. Box 944246
Sacramento, CA 94244-2460
fhszcomments@fire.ca.gov

RE: Notice of Proposed Rulemaking Action (NOPA), California Code of Regulations, Title 19, Division 1, Chapter 17, relating to the classifying of lands in the State Responsibility Area (SRA) into Fire Hazard Severity Zones (FHSZs).

Dear Office of the State Fire Marshal:

The Tuolumne County Board of Supervisors appreciates the opportunity to comment on the notice to adopt proposed regulations pursuant to Public Resources Code (PRC) Sections 4202-4204, relating to the classifying of lands in the State Responsibility Area (SRA) into Fire Hazard Severity Zones (FHSZs).

Tuolumne County is a forestry-and tourism-based small economy located in the foothills of the Sierra Nevada mountains and has the same interest as the Office of the State Fire Marshal in reducing loss of life and property from catastrophic fires. However, the County must balance that common goal with the priorities of ongoing residential growth and by promoting a healthy local economy. The framework of this is accomplished via thoughtful land use regulation, as almost all of the County is located either in the SRA or VHFHZ, the County recognizes that much of its development guidelines hinge on the details and designation of fire severity zones within the county. If those regulations change severity zones within certain communities, population growth in the County will stagnate, with no future here for the next generations of Tuolumne County to look forward to. The County is already severely limited in its development potential, with only 22.64% of lands in private ownership. The remaining 77.36% of lands, mostly comprised of National Forest, BLM, or National Parks lands, are in public ownership.

As the County seeks to reduce fire risk, the proposed regulations appear, at least in part, to slightly increase the amount of acreage of very high and high designations, thus potentially impacting a need to consider them in updating and implementing our general plan. The Tuolumne County General Plan encourages development within certain areas of the County that have available infrastructure and are not located within a very high or high zone as based on the previous severity designations. A change and increase in the areas designated would contradict the General Plan in the Goals, Policies, and Implementation Programs to direct future growth and development within certain areas. This would further limit the areas of the county that are feasible and recommended for future growth based on the General Plan.

Tuolumne County does object to the science-based modelling of how these designations were made as it does not apply to our local area. There are several communities that have an increase of severity while literal neighbors with steeper slope do not. While we understand that insurance companies use risk models (not hazard) and the Insurance Commissioner has publicly stated that fire severity zones are not used in determining risk, we would like local area data to be considered. Per a recent study conducted by a retired USFS GIS Specialist and local College Instructor, Jim Schmidt, in his paper titled and attached "Defensible Space, Housing Density and Diablo -North Wind Events: Impacts on loss rates for homes in Northern California Wildfire", high-wind events during the fire season are much more common in the San Francisco Bay Area (called Diablo Winds) and in the Sierras north of Lake Tahoe (called North Winds). These types of winds are rare in Tuolumne County during the fire season. No instances of such winds were found in the last 20 years at the Mt. Elizabeth or Bald Mountain weather stations and only one event at the Green Springs weather station. We request that local data be used for the hazard model and severity designations.

While we appreciate the broad objective to ensure that the people of California understand the degree of severity of fire hazard that is expected to prevail in the zone in which they live, implementation of measures that will reduce the potential for losses to life, property and resources from wildfire will come at a cost to both private individuals and the local government that must implement such measures. We ask that you consider efforts that our communities, individual property owners and our County have already taken to prevent/mitigate wildfire by eliminating the hazards that increase wildfires. Measures such as hazardous fuels reduction, creation of Firewise communities, management of millions of dollars of grant funds to implement the Master Stewardship Agreement or Social and Ecological Resilience Across the Landscape (SERAL) project, and roadside brushing along key access routes. All the work that we have accomplished and have identified as a priority within our community should be considered as actually eliminating those hazards that the modeling has identified for severity zone designations.

In closing, while we understand that insurance companies use risk models (not hazard), and that the Insurance Commissioner has publicly stated that fire severity zones are not used in determining risk. Tuolumne County currently has the highest number of California Fair Plan policies, and we cannot continue with such impacts. Tuolumne County has the highest percentage of insurance per capita on the Fair Plan in the State, at 31.9% yet our community has lost the least number of homes, especially when compared to other counties throughout the state. Any changes to perceived risk or severity designations by insurance companies will likely increase insurance premiums for our community. Please consider our request in using local data and the measures we have taken to reduce the hazards for wildfire in our community.

Thank you for your time and consideration of the Board's comments. Should you have any questions regarding our comments or wish to discuss our concerns further, please feel free to reach out.

Sincerely,

K Haff

Supervisor Kathleen K. Haff
Chair, Tuolumne County Board of Supervisors

Cc: RCRC
CSAC
California Assembly Member Jim Patterson
California State Senator Marie Alvarado-Gil

Attachment(s)

I hereby certify that according to the provisions of Government Code Section 25103, delivery of this document has been made.

TANYA BRUCHACEK
Executive Clerk
By: Tanya Bruchacek

Defensible Space, Housing Density, and Diablo-North Wind Events: Impacts on Loss Rates for Homes in Northern California Wildfires

Abstract: If a house is exposed to a wildfire, what is the probability that it will be destroyed? How is the risk of loss affected by vegetation cover near the home (i.e., defensible space), the proximity to other homes, and wind levels? This study addresses these questions with an analysis of 36,777 single-family homes involved in ten recent Northern California wildfires. Two logistic regression models are constructed, one for Diablo-North Wind (DNW) fires and another for fires with more moderate winds. Vegetation cover within 50 meters and housing density within 100 meters of each house are identified as statistically significant variables. But the models including those two variables alone are relatively weak predictors of structure loss. The addition of an autocovariate derived from the outcomes for nearby houses substantially improves prediction accuracy. The autocovariate partially accounts for events during fires, such as wind changes or structure-to-structure fire spread, which influence the fate of multiple homes in close proximity. The effect on classification accuracy is illustrated for the Coffee Park neighborhood in the 2017 Tubbs Fire.

Increases in housing density appear to have little effect on loss rates in moderate wind fires, but can raise loss rates by 35% in DNW fires. A 10% reduction in vegetation cover near homes is estimated to reduce loss probability by 4-6% in most situations, but by only 1-2% when high winds are combined with high housing density. Loss rates are 20-60% higher in DNW fires compared to moderate wind fires for the same levels of vegetation cover and housing density. Previous studies and Red Flag Warning data indicate that the San Francisco Bay Area is most at risk for Diablo-North winds, followed by the Northern Sierras. The higher elevations found in the Sierras south of Lake Tahoe tend to reduce the chances for DNW-type events.

1.Introduction

In the decade from 2012 through 2021, wildfires burned over 10.8 million acres in Northern California, compared to 2.8 million acres in the previous decade. 48,000 structures were destroyed and more than 125 lives were lost. As exposure to wildfire rises, the factors that contribute to structure loss are of growing concern to homeowners, insurers, fire fighters and regulatory agencies. This study examines the influence of several variables on loss rates for single-family homes in wildfires: vegetation near structures, structure density, and wind levels. The ten fires included in the analysis account for 82% of the single-family residences destroyed by wildfires in Northern California during the 2012-2021 decade. Table 1 lists the fires included in the study along with selected statistics. Figure 1 displays the fire locations.

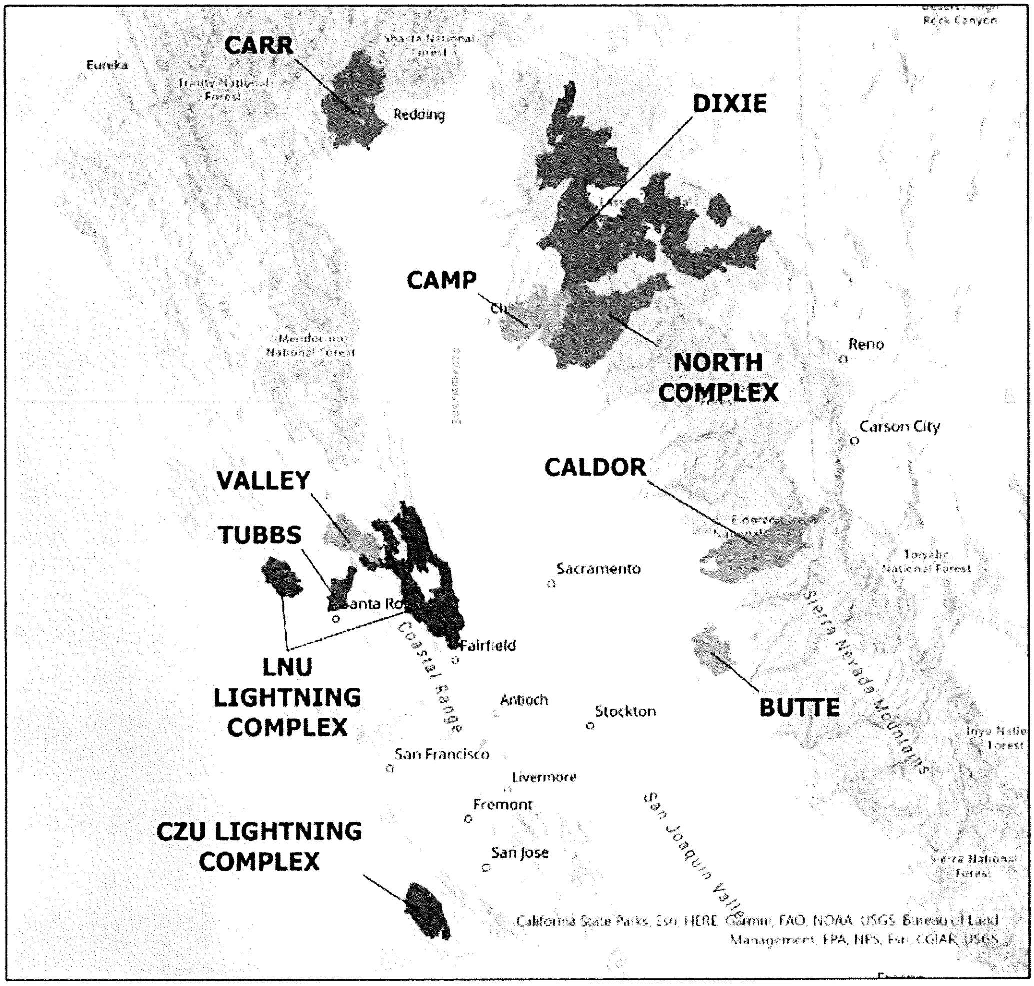
Table 1. Statistics by Fire

FIRE NAME	START DATE	SINGLE FAMILY RESIDENCES	DESTROYED	LOSS RATE	VEG. COVER* (pct)	HOUSING DENSITY** (per ac.)	MAX. WIND (mph)
BUTTE	Sept. 9, 2015	1,262	654	0.52	57.4	0.19	22
VALLEY	Sept. 12, 2015	2,307	1,285	0.56	37.5	0.97	43
TUBBS	Oct. 8, 2017	5,599	4,530	0.81	39.1	2.47	68
CARR	July 23, 2018	2,189	1,101	0.50	45.8	0.90	21
CAMP	Nov. 8, 2018	16,201	13,500	0.83	59.4	1.86	52
CZU LTNG. COMPLEX	Aug. 16 2020	1,964	915	0.47	71.9	0.72	34
LNU LTNG. COMPLEX	Aug. 16, 2020	2,173	787	0.36	34.7	0.62	32
NORTH COMPLEX	Aug.17, 2020	1,534	1,172	0.76	72.0	0.36	66
DIXIE	July 13, 2021	1,616	668	0.41	53.5	0.94	37
CALDOR	Aug. 14, 2021	1,932	783	0.41	75.2	0.94	33
TOTAL		**36,777**	**25,395**	**0.69**	**54.3**	**1.5**	**48**

* Average vegetation cover within 50 meters of a point representing each house.

** Based on the number of houses within 100 meters of each house point.

Figure 1: Northern California Wildfires Included in Study



2. Previous Studies

Empirical studies attempting to assess the effect of vegetation near structures on wildfire losses have had mixed results. Several studies using high-resolution aerial imagery or LIDAR to measure vegetation (Gibbons et al., 2012; Syphard et al., 2014; Schmidt, 2020; Schmidt, 2022; Knapp et al., 2021) have found that vegetation cover within 25 to 100 meters of a structure has a significant effect on structure loss. Studies relying on ground-based estimates of defensive space compiled by the California State Department of Forestry and Fire Protection (Syphard et al., 2017; Troy et al., 2022) have identified only a weak relationship between vegetation near homes and structure loss. Syphard et al. (2021) found that vegetation near homes derived from 30-meter resolution LANDSAT satellite imagery was a poor predictor of structure loss in Northern California.

Studies examining the effects of structure density have also had mixed results. Proximity to neighboring structures was found to be positively related to structure loss rates in Gibbons et al. (2012) and Schmidt (2022). In Knapp et al. (2021) distance to the nearest burned structure was identified as the strongest predictor of structure loss for the Camp fire. Syphard et al. (2014) and Alexandre et al. (2016) found that structure density was negatively related to structure loss in Northern California. Kramer et al. (2019) and Syphard et al. (2021), however, noted that Wildland-Urban Interface (WUI) categories with higher structure density had a higher relative risk of loss.

Gibbons et al. (2012) indirectly analyzed the effect of wind speeds on structure loss rates. In that study a Forest Fire Danger Index value, which included wind speed, was the second most significant predictor of loss rates for 499 houses sampled after the 2009 Black Saturday fires in Australia. Schmidt (2022) found that maximum wind speed recorded on the day of greatest structure loss was a significant predictor of loss rates in nine Northern California wildfires.

3. Materials and Methods

3.1 Structure Loss and Structure Density

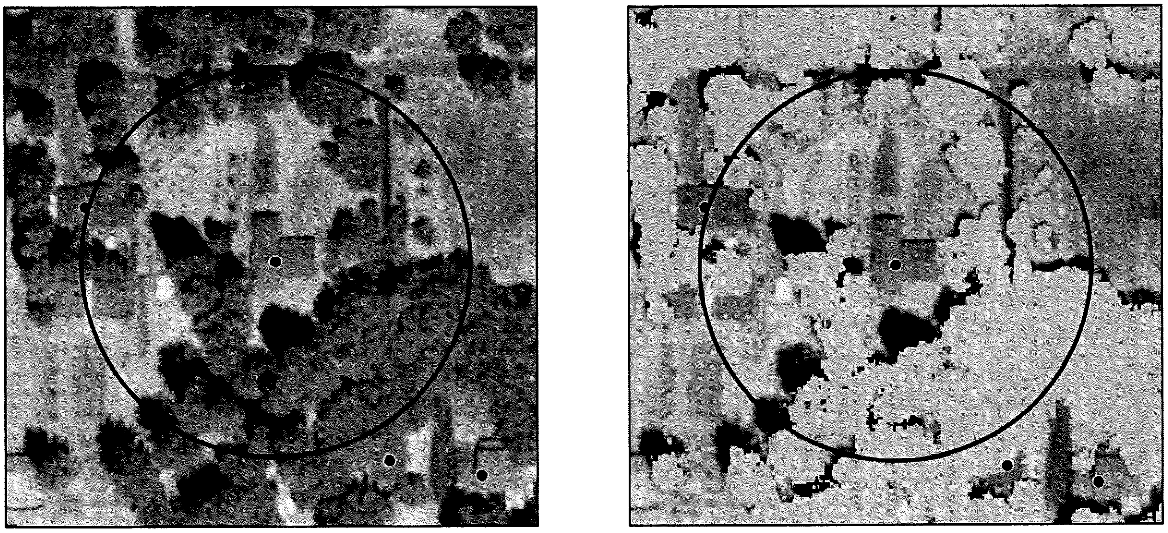
The Damage Inspection database (DINS) compiled by Cal Fire is the primary source for structure locations and damage. The DINS database records the coordinates of a point representing each structure inspected after a wildfire, an assessment of the damage to the structure, and selected structure characteristics. In the current study all structures identified as single-family residences in the DINS data are included, except for motor homes. Structures with more than 10% recorded damage are counted as a loss.

Undamaged houses not included in the DINS database are added using pre-fire aerial imagery from the National Agricultural Imagery Program (NAIP) (https://gdg.sc.egov.usda.gov/) and building footprint data from Microsoft (https://www.microsoft.com/en-us/maps/building-footprints). Of the 36,777 houses in the study dataset, 33,002 (90%) are derived from the DINS database and 3,775 (10%) from other sources. The locations of DINS structure points were adjusted, when necessary, to match the structure locations in the NAIP imagery and the Microsoft data. 40% of the DINS structure points were re-positioned by at 5 meters or more. Only houses located within mapped fire boundaries are included in the dataset. Fire boundaries are taken from the 2021 Cal Fire dataset found at: https://frap.fire.ca.gov/mapping/gis-data/. Structure densities are calculated from the number of neighboring house points counted within 100 meters of each house point. The 100-meter zone encompasses the 300 ft. distance that embers are known to travel from burning residential structures and to ignite other structures (Maranghides et al., 2022).

3.2 Vegetation Cover

High resolution (0.6-1.0 meter pixel size) pre-fire infrared NAIP imagery is used to estimate live vegetation cover within 50 meters of each structure point. The 50-meter zone approximates the 100 ft. defensible space distance defined by California state law. A Normalized Difference Vegetation Index (NDVI) is calculated for each pixel in the NAIP images. Pixels with an NDVI value of 0.25 or less are classified as non-vegetation and pixels with an NDVI greater than 0.25 are classified as vegetation. Vegetation cover is estimated from the percent of pixels classified as vegetation within the 50-meter circle around each structure point. Figure 2 illustrates the procedure:

Figure 2: Example Vegetation Cover Calculation



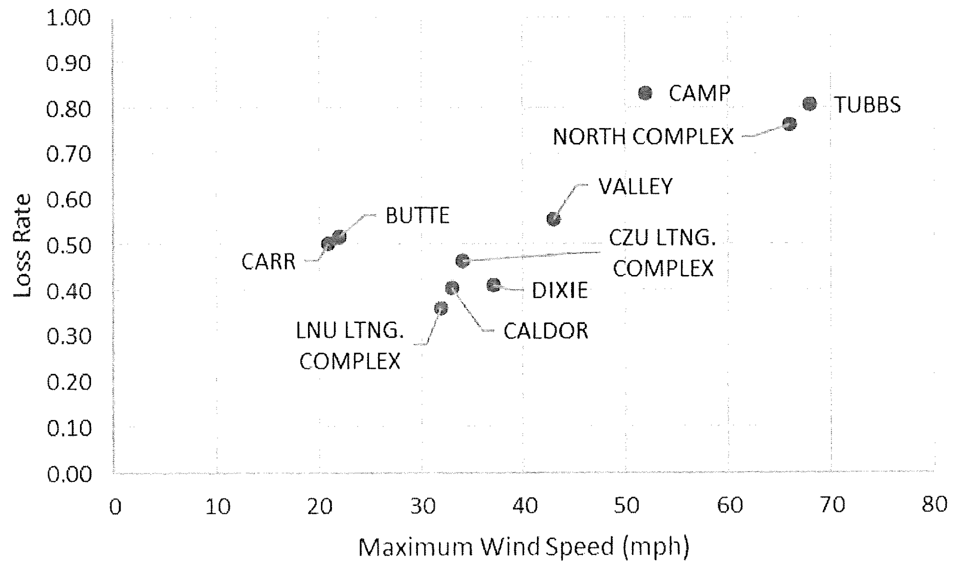
The image on the left is the original infrared NAIP image with a 50-meter circle drawn around a point representing the structure. The image on the right shows the area classified as live vegetation in green. In this example, the green area within the 50-meter circle amounts to 49% of the area within the circle.

3.3 Wind Classification

Strong, dry, gusty downslope winds from the north or northeast that originate from the Great Basin deserts are associated with some of the most destructive and deadliest fires in California history (Keeley and Syphard, 2019). These winds are labelled "Santa Ana Winds" in Southern California, "Diablo Winds" when they occur in the San Francisco Bay Area, "North Winds" in the Northern Sierras and "Mono Winds" in Central and Southern Sierras.

According to Smith et al. (2018) and Nausler et al. (2018), the 2017 Tubbs Fire in Santa Rosa occurred during a Diablo Wind event. The 2018 Camp Fire in Paradise was associated with a North Wind event (Brewer and Clements, 2019; McClung and Mass, 2020). The structure losses in the North Complex fire occurred during a North Wind event on Sept. 8, 2020, according to data recorded by the Remote Automated Weather Station (RAWS) at Jarbo Gap (RAWS USA Climate Archive, 2023). Figure 3 displays the maximum wind speeds and loss rates for each fire in this study as displayed in Table 1. Maximum wind speeds are taken from nearby RAWS data. The three DNW fires have both the highest recorded maximum winds and the highest loss rates. Loss rates averaged 82% for the DNW fires compared to 46% for the fires with more moderate winds.

Figure 3: Loss Rates by Fire vs. Maximum Recorded Winds



4. Analysis

4.1 Housing Density and Loss Rates

Burning structures can pose a hazard to other structures in wildfires, igniting nearby homes through direct flame, radiant heat, or ember transport (Cohen, 1995). Those effects are magnified by strong winds which increase both fire intensity and the size and distance travelled by embers (Maranghides et al., 2022).

Table 2 and Figure 4 display loss rate statistics for homes grouped by Housing Density Class and Wind Category. Housing Density Class 0 includes those homes having no other houses within 100 meters (i.e., a density of one house per 7.8 acres). Density Class 1 includes those homes having 1 to 5 neighboring homes within 100 meters; Density Class 2 includes homes with 6-10 neighbors, etc. Density Class 10 includes all homes with a density of more than 45 homes in the 100-meter zone. Due to low numbers, Housing Density Classes 6-10 for moderate wind fires are combined in Figure 4. Wind Categories include Moderate Wind and DNW.

In the Moderate Wind Category, loss rates average 45% when there are no other houses within 100 meters (Housing Density Class 0). Loss rates remain at that level through Density Class 2 (6-10 neighboring houses or 0.9-1.4 houses per acre). At higher housing density levels, loss rates increase slightly, but not in a consistent pattern. In contrast, loss rates for DNW fires start out at 65% for Density Class 0 and rise rapidly, reaching 89% for Housing Density Class 3 (11-15 neighboring houses or 1.5-2.0 houses per acre) and remaining near 90% for all higher housing densities.

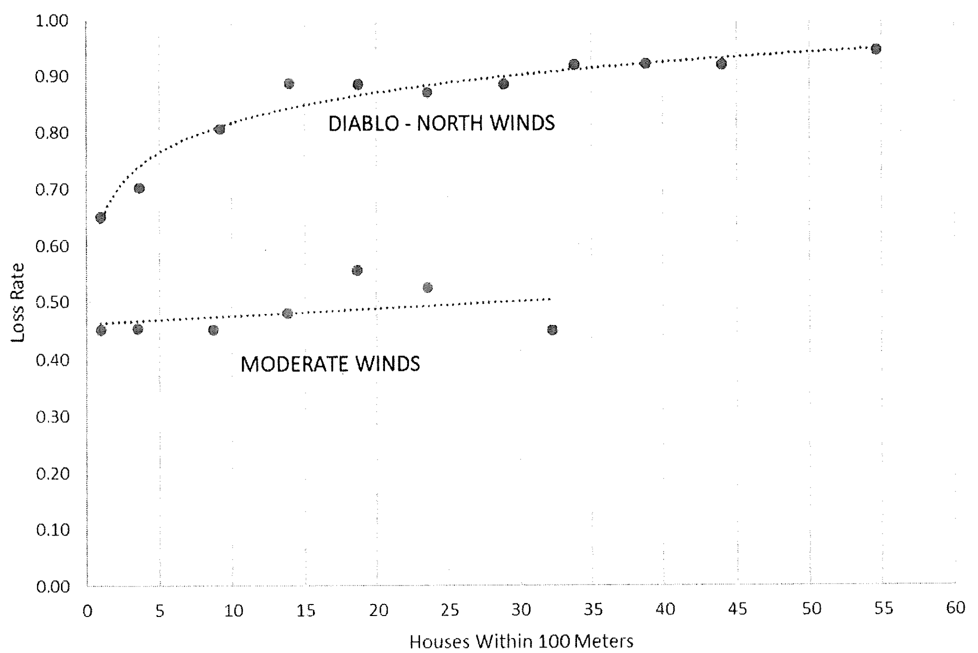
Table 2: Loss Rates by Housing Density Class and Wind Category

	MODERATE WINDS				DIABLO-NORTH WINDS			
CLASS	COUNT	HOUSES*	VEG. COVER**	LOSS RATE	COUNT	HOUSES*	VEG. COVER**	LOSS RATE
0	3168	1.0	50.5	0.45	1840	1.0	55.3	0.65
1	5858	3.5	56.5	0.45	4336	3.6	58.3	0.70
2	2124	8.7	54.1	0.45	3925	9.2	60.3	0.81
3	1242	13.9	47.0	0.48	4935	13.9	60.9	0.89
4	645	18.7	45.4	0.56	3514	18.7	58.0	0.89
5	250	23.6	38.1	0.52	1731	23.6	55.2	0.87
6	86	28.6	33.1	0.44	864	28.9	41.1	0.89
7	46	34.2	25.0	0.59	689	33.8	36.6	0.92
8	15	39.2	29.8	0.33	517	38.8	33.1	0.92
9	5	42.4	28.1	0.00	401	44.0	26.4	0.92
10	4	49.3	35.6	0.00	582	54.6	20.1	0.95
Classes 6-10	156	32.3	30.3	0.45				
Total	**13443**	**3.8**	**52.6**	**0.46**	**23334**	**14.9**	**55.3**	**0.82**

* Average number of houses within 100 meters

** Average percent vegetation cover within 50 meters

Figure 4: Loss Rates by Housing Density Class and Wind Category



4.2 Vegetation Cover and Loss Rates by Density-Wind Categories

Table 3 and Figure 5 display loss rates by Vegetation Cover Class and Housing Density-Wind Category. Vegetation Cover Class 1 includes houses with 0-10% vegetation cover in the 50-meter zone. Vegetation Cover Class 2 includes houses with vegetation cover from 10 to 20%, etc. Two housing density categories are combined with two wind categories. The Low Housing Density Category includes those houses with a density of up to 15 houses in the 100-meter zone (2 houses per acre or less). The High Housing Density Category includes houses with more than 15 houses in the 100-meter zone (> 2 houses per acre). Wind categories are: Moderate Wind and DNW.

For homes in the Moderate Wind – Low Housing Density Category (Curve A in Figure 5) loss rates rise relatively slowly as vegetation cover increases and never exceed 55%. For homes in the DNW-Low Housing Density Category (Curve B in Figure 5) losses rise rapidly as vegetation cover increases, reaching 80% with 55% vegetation cover. Curve C in Figure 5 displays loss rates for the DNW - High Housing Density Category. Loss rates are 84% or higher, even for homes with very low vegetation cover.

(Note: There are relatively few homes in the Moderate Wind - High Housing Density Category (1,051). Loss rates by vegetation class for that category do not follow a consistent pattern and are not graphed in Figure 5).

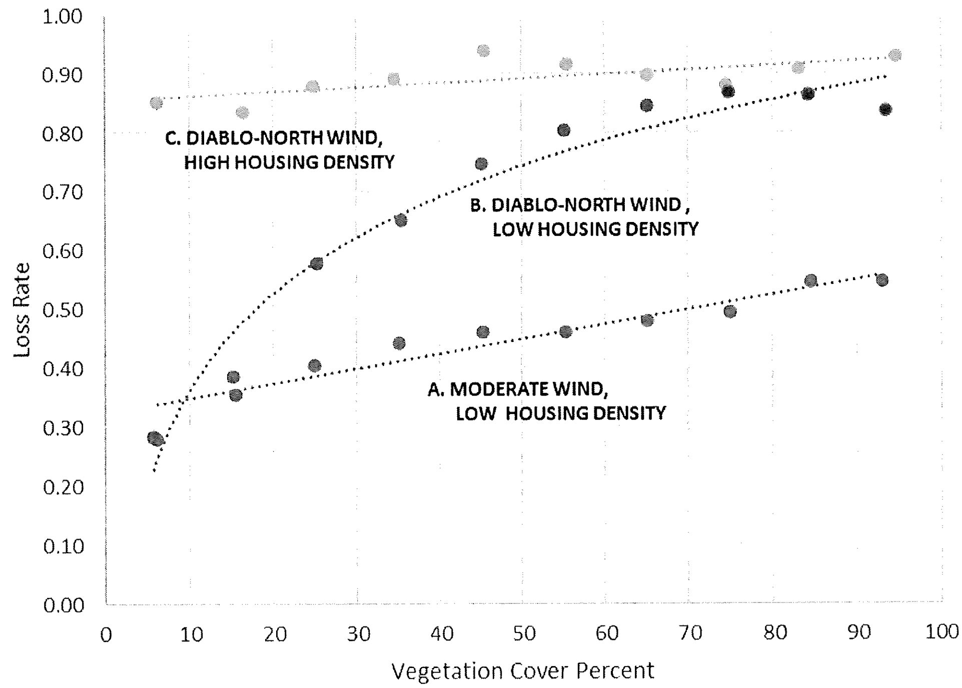
Table 3. Loss Rates by Vegetation Class and Wind-Housing Density Categories

	MODERATE WIND-LOW HOUSING DENSITY (CURVE A)				MODERATE WIND-HIGH HOUSING DENSITY (NOT GRAPHED)			
VEG. CLASS	**COUNT**	**DENSITY***	**VEG. COVER****	**LOSS RATE**	**COUNT**	**DENSITY***	**VEG. COVER****	**LOSS RATE**
1	497	4.1	6.2	0.28	50	22.5	6.9	0.34
2	948	5.2	15.3	0.39	99	21.8	16.1	0.62
3	1,213	5.8	25.0	0.40	249	22.7	25.1	0.51
4	1,185	5.0	35.1	0.44	228	24.5	34.8	0.54
5	1,369	4.2	45.2	0.46	93	20.2	44.0	0.71
6	1,523	4.4	55.2	0.46	63	20.1	54.9	0.75
7	1,821	4.7	65.1	0.48	98	20.0	65.4	0.42
8	1,901	5.0	75.0	0.49	111	20.0	74.7	0.46
9	1,474	4.9	84.5	0.55	44	19.0	84.4	0.50
10	461	3.8	93.0	0.55	16	18.8	92.3	0.31
TOTALS	**12,392**	**4.8**	**53.6**	**0.46**	**1,051**	**21.9**	**41.4**	**0.53**
	DNW-LOW HOUSING DENSITY (CURVE B)				**DNW-HIGH HOUSING DENSITY (CURVE C)**			
VEG. CLASS	**COUNT**	**DENSITY***	**VEG. COVER****	**LOSS RATE**	**COUNT**	**DENSITY***	**VEG. COVER****	**LOSS RATE**
1	165	2.5	5.8	0.28	189	60.3	6.2	0.85
2	394	4.3	15.6	0.36	625	38.4	16.4	0.84
3	754	6.3	25.3	0.58	1,491	33.8	24.8	0.88
4	1,284	7.7	35.4	0.65	893	27.2	34.6	0.89
5	1,957	8.5	45.2	0.75	853	23.8	45.3	0.94
6	2,441	8.7	55.2	0.80	1,245	23.0	55.4	0.92
7	3,025	9.2	65.1	0.85	1,498	22.2	65.1	0.90
8	2,884	8.8	74.8	0.87	1,170	21.5	74.4	0.88
9	1,638	7.4	84.3	0.86	306	20.8	83.0	0.91
10	494	5.1	93.5	0.84	28	19.6	94.7	0.93
TOTALS	**15,036**	**8.1**	**59.3**	**0.78**	**8,298**	**27.0**	**48.2**	**0.89**

* Average number of houses within 100 meters.

** Average percent vegetation cover within 50 meters.

Figure 5. Loss Rates by Wind - Housing Density Categories and Vegetation Cover Class



4.3 Logistic Modelling

Two logistic regression models are estimated to evaluate the combined effects of vegetation cover and housing density on loss rates: one model for moderate wind fires and one for DNW fires. In both models, the dependent variable is set to 1 for a structure loss and to 0 for a structure survival. Independent variables are: HOUSE100 - the number of houses within 100 meters of each single-family residence, including the residence itself; and VEG50_PCT - the percentage of vegetation cover within 50 meters. The models are estimated for 13,443 homes in moderate wind fires and 23,334 homes in DNW fires.

Tables 4 and 5 display initial results for the two models. The VEG50_PCT and HOUSE100 variables are significant for both models at the 99% confidence level. The model coefficient for VEG50_PCT is about three times higher in DNW fires compared to moderate wind fires. The coefficient for HOUSE100 is more than 4 times higher in the DNW model.

The Area Under the Receiver Curve (AUC) is only 0.569 for the moderate wind logistic model, indicating that the model is a poor predictor of structure loss. That compares to an AUC of 0.702 for the DNW model, just over the limit of what qualifies as acceptable (Hosmer, et al., 2013). For moderate wind fires only 34% of houses that burned were correctly classified (predicted loss probability > 0.50). Of those houses that survived, 73.2% were correctly classified (predicted loss probability < 0.50). Those results yield an average classification accuracy of 55.1%. For DNW fires, the classification accuracy for burned structures is an excellent 98.8%. But the accuracy for surviving houses is only 10%, for an average classification accuracy of 83%. The Moran's I statistic for residuals in both the moderate wind fires and the DNW fires shows a moderate level of spatial autocorrelation which gradually decreases with distance.

Table 4. Initial Logistic Model - Moderate Wind Fires

VARIABLE	COEFF	S.E.	WALD	P-VALUE
intercept	-0.7682	0.0479	256.8	0.0000
VEG50_PCT	0.0098	0.0007	182.1	0.0000
HOUSE100	0.0148	0.0028	27.3	0.0000
AUC	0.569			

	Classification Accuracy		
	Lost	**Survived**	**Total**
Houses	6,192	7,251	13,443
Correct Classification	34.0%	73.2%	55.1%

Moran's I Statistic		
100m	**200m**	**1000m**
0.611	0.523	0.337

Table 5. Initial Logistic Model - Diablo-North Wind Fires

VARIABLE	COEFF	S.E.	WALD	P-VALUE
intercept	-0.8783	0.0588	223.0	0.0000
VEG50_PCT	0.0288	0.0009	1007.9	0.0000
HOUSE100	0.0682	0.0020	1200.6	0.0000
AUC	0.702			

	Classification Accuracy		
	Lost	**Survived**	**Total**
Houses	19,202	4,132	23,334
Correct Classification	98.8%	10.0%	83.0%

Moran's I Statistic		
100m	**200m**	**1000m**
0.391	0.287	0.145

To address the effects of spatial autocorrelation on predicted outcomes, an autocovariate is added to the logistic models. The autocovariate is based the residuals from the initial logistic models described Tables 4 and 5, following Crase et al. (2012). Houses that burned will have a negative residual while houses that survived will have a positive residual. The autocovariate calculated here is the sum of the inverse distance-weighted residuals for all houses within 100 meters, multiplied by 100. For those houses having no neighboring houses within 100 meters, the autocovariate is set to zero. The result of adding this variable (AUTOCOV) to the models is displayed in Tables 6 and 7.

The autocovariate has a large impact on the AUC for the moderate wind fires, increasing it from 0.569 to 0.870. The improvement in AUC for DNW fires is smaller, but still substantial, rising from 0.702 to 0.885. Classification accuracy also shows significant improvement. Model coefficients for VEG50_PCT increase slightly. The coefficient for HOUSE100 almost doubles for the DNW model but switches to a small negative number for the moderate wind model. The Moran's I statistic drops to very low levels indicating little remaining spatial autocorrelation in either model.

Table 6. Logistic Model with Autocovariate - Moderate Wind Fires

VARIABLE	COEFF	S.E.	WALD	P-VALUE
intercept	-1.0634	0.0589	325.8	0.0000
VEG50_PCT	0.0175	0.0009	359.3	0.0000
HOUSE100	-0.0244	0.0067	13.3	0.0003
AUTOCOV	-0.4977	0.0113	1938.4	0.0000
AUC	0.870			
	Classification Accuracy			
	Lost	**Survived**	**Total**	
Houses	6,192	7,251	13,443	
Correct Classification	72.7%	83.4%	78.5%	
	Moran's I Statistic			
	100m	**200m**	**1000m**	
	0.022	0.172	0.128	

Table 7. Logistic Model with Autocovariate - Diablo-North Wind Fires

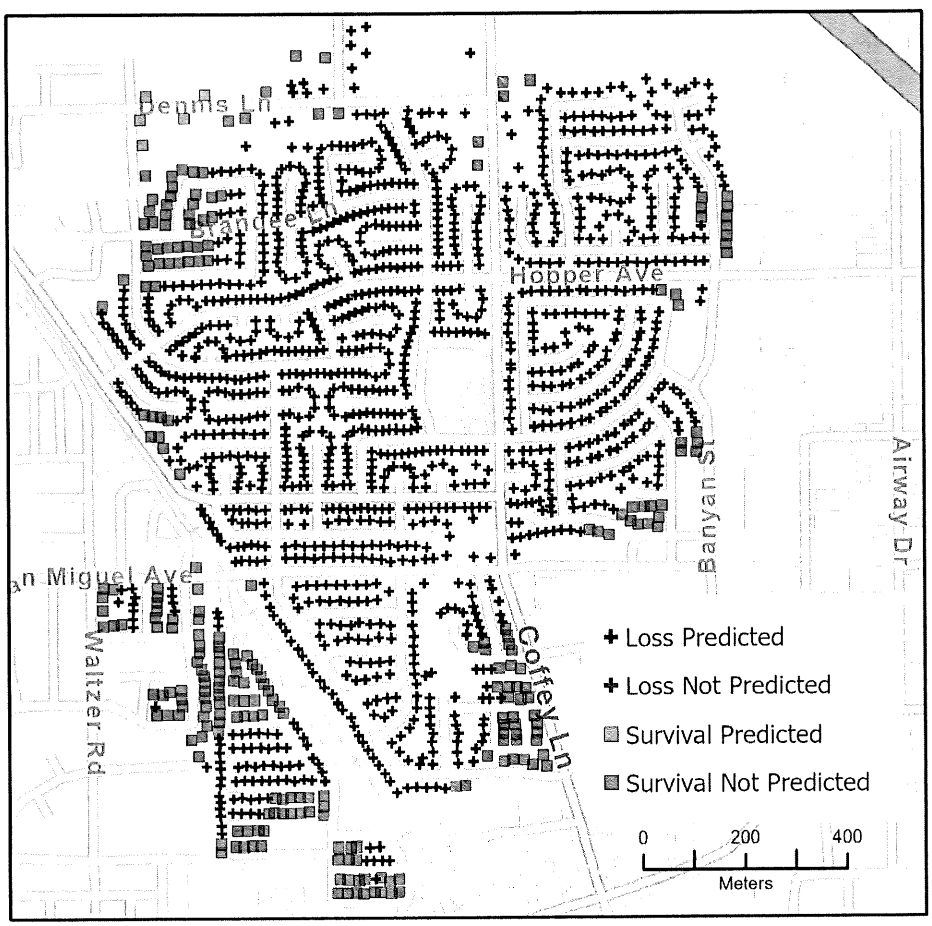
VARIABLE	COEFF	S.E.	WALD	P-VALUE
intercept	-1.1601	0.0661	308.4	0.0000
VEG50_PCT	0.0270	0.0010	675.3	0.0000
HOUSE100	0.1451	0.0034	1798.9	0.0000
AUTOCOV	-0.2952	0.0059	2521.3	0.0000
AUC	0.885			
	Classification Accuracy			
	Lost	**Survived**	**Total**	
Houses	19,202	4,132	23,334	
Correct Classification	97.1%	45.4%	87.9%	
	Moran's I Statistic			
	100m	**200m**	**1000m**	
	0.062	0.113	0.086	

4.4 Coffee Park Example

The autocovariate incorporates the fate of neighboring houses in predicting structure survival. When nearby houses have burned, the autocovariate will tend to increase the predicted loss rate. When nearby houses have not burned, the autocovariate will tend to decrease the predicted loss probability. In effect, the autocovariate represents the that portion of structure loss or survival which can be attributable to local spatial patterns that are not explained by vegetation cover near homes and housing density.

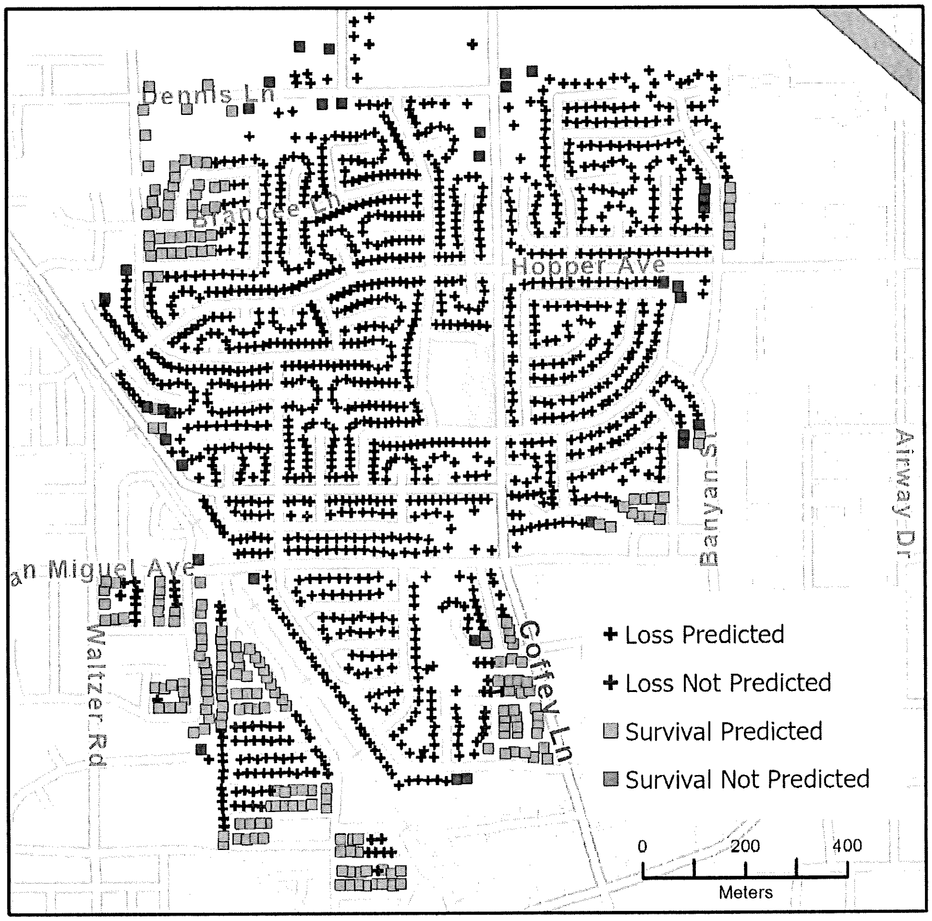
A map of predicted vs. actual losses for the Coffee Park neighborhood in the Tubbs Fire (Figure 7) illustrates the spatial clustering that exists in classification results from the initial DNW model in Table 5. The red squares represent houses that were predicted to be losses but which survived. The pattern of structure loss and survival suggests that the fire initially started in the interior of the development from ember ignition, and then spread outward from house-to-house. The outward spread most likely came to a stop either because wind levels subsided or wind direction changed or because of defensive efforts by fire fighters (or perhaps some combination of these factors). The clustering exhibited in the location of surviving structures does not point to structure hardening as the primary reason for structure survival in this instance.

Figure 7: Predicted vs. Actual Losses, No Autocovariate, Coffee Park, Tubbs Fire



The map in Figure 8 displays the predicted loss results for the Coffee Park neighborhood when the autocovariate is added to the DNW model (Table 7). Most of the red squares that appeared in Figure 7 have changed to green, indicating that those houses are now correctly predicted to survive due to their proximity to other surviving houses. (There are also a few red crosses identifying houses that are now incorrectly predicted to survive).

Figure 8: Predicted vs. Actual Losses with Autocovariate, Coffee Park, Tubbs Fire



4.5 Sensitivity Analysis

Table 8 displays the predicted loss rates using the enhanced logistic models in Tables 6 and 7 for selected combinations of housing density and vegetation cover and with the AUTOCOV variable set to 0. The housing densities listed are 3.9, 7.8 and 15.6 houses within the 100-meter zone, representing 0.5, 1, and 2 houses per acre, respectively. Predicted loss rates range from 31% when housing density and vegetation cover are low and winds are moderate to 96% when housing density, vegetation cover, and winds are high. Most housing density – vegetation cover combinations have an expected loss rate below 50% in the moderate wind fires, except when vegetation cover exceeds 80%. For DNW fires, only houses with 20% vegetation cover and a density of 0.5 houses per acre have less than a 50% predicted loss rate.

Housing density appears to have little effect on loss rates in moderate wind fires, but for DNW fires, loss rates at high densities exceed those at low densities from 13-35%. Compared to moderate wind fires, DNW fires have loss rates that are about 20-25% higher than moderate wind fires for the same vegetation cover classes. At housing densities of 2 houses per acre, loss rates for DNW fires are 45-60% higher.

Table 8: Predicted Loss Rates

		Moderate Wind Fires		
HOUSE100	**HOUSES PER ACRE**	**20% VEG COVER**	**50% VEG COVER**	**80% VEG COVER**
3.9	0.5	0.31	0.43	0.56
7.8	1	0.29	0.41	0.54
15.6	2	0.25	0.36	0.49
		Diablo-North Wind Fires		
HOUSE100	**HOUSES PER ACRE**	**20% VEG COVER**	**50% VEG COVER**	**80% VEG COVER**
3.9	0.5	0.49	0.68	0.83
7.8	1	0.63	0.79	0.89
15.6	2	0.84	0.92	0.96

Table 9 displays the rate of change in predicted loss rate for each 10% change in vegetation cover near homes based on the data in Table 8. There is little variation in moderate wind fires. A 10% change in vegetation cover produces a change in loss rates of about 4% for each housing density – vegetation cover change category. When housing density is one house per acre or less and vegetation cover is less than 50%, loss rates in DNW fires show a larger response to vegetation cover change (5.5-6.5%). But with housing density at 2 houses per acre, a 10% vegetation cover change produces only a 1.4-2.8% change in loss rates in DNW fires.

Table 9: Per Cent Change in Predicted Loss Rate for Each 10% Change in Vegetation Cover

		Moderate Wind Fires	
HOUSE100	**HOUSES PER ACRE**	**VEG COVER CHANGE 20% TO 50%**	**VEG COVER CHANGE 50% TO 80%**
3.9	0.5	4.0%	4.3%
7.8	1	3.9%	4.3%
15.6	2	3.7%	4.2%
		Diablo-North Wind Fires	
HOUSE100	**HOUSES PER ACRE**	**VEG COVER CHANGE 20% TO 50%**	**VEG COVER CHANGE 50% TO 80%**
3.9	0.5	6.5%	4.9%
7.8	1	5.5%	3.5%
15.6	2	2.8%	1.4%

4.6 Location and Frequency of Diablo-North Wind Events

In the 2012-2021 decade, there were four large Diablo Wind fires, the so-called Wine Country fires of 2017: Tubbs, Atlas, Redwood, and Nuns (San Jose State Fire Weather Research Laboratory, https://www.fireweather.org/diablo-winds). Two large North Wind fires occurred in the same period: the Camp Fire in 2018 (Brewer and Clements, 2018) and the North Complex Fire in 2020. In total, these six DNW fires accounted for only 7% of the acres burned in Northern California in the last decade but two-thirds of the single-family residences destroyed. As seen in Table 8, the predicted loss rates in DNW fires are 20 to 60 percentage points higher compared to moderate wind fires. A comprehensive evaluation of risk of structure loss in wildfires should take into account the frequency and location of a DNW events and the likelihood that a fire would result from those events.

Using weather station data for 11 RAWS for the 2001-2018 time period, Smith et al. (2018) found that DNW events averaged 2.5 times a year during the late summer and fall in the San Francisco Bay Area and the western slopes of the Northern Sierras. Employing a larger number of weather stations (47) and slightly different criteria, McClung and Mass (2020) counted almost twice as many Diablo wind events in the Bay Area (8.0 per year) compared to North wind events in the Sierras (4.5 per year). McClung defined a DNW event as a 3-hour period with a relative humidity less than 20%, an average wind speed greater than 13 ms^{-1} (29 mph), a surface wind direction of 320°-70° for the Bay Area weather stations and a surface wind direction of 10°-100° for Sierra Nevada weather stations.

The frequency of Diablo-North type winds in the Central and Southern Sierras (aka "Mono Winds") has received less study. Ruscha (1976) suggests that east winds are less frequent in the High Sierras south of Lake Tahoe compared to the lower elevations found in the Northern Sierras and in the very southern part of the range. He estimates that Mono Winds occur once or twice a year, starting in September, but most often in December or January.

Red Flag Warnings (RFWs) are issued by the National Weather Service when it forecasts that warm temperatures, low fuel moisture, low humidity, and strong winds will increase fire danger. RFWs are not equivalent to DNW or Mono Wind events. Table 10 shows that RFWs can be issued for winds as low as 6 mph, if relative humidity is less than 9%. But the average annual number of RFWs in the late summer and fall gives a general indication of how frequently dry and windy conditions develop during the time of year when DNW fires have happened.

Table 10: Criteria for Red Flag Warnings, Northern California, West of the Cascade-Sierra Crest

Relative Humidity	Sustained Wind 6-11 mph	Sustained Wind 12-20 mph	Sustained Wind 21-29 mph	Sustained Wind 30+ mph
Daytime Minimum RH 29-42% and/or Nighttime Maximum RH 60-80%				W
Daytime Minimum RH 19-28% and/or Nighttime Maximum RH 46-60%			W	W
Daytime Minimum RH 9-18% and/or Nighttime Maximum RH 31-45%		W	W	W
Daytime Minimum RH < 9% and/or Nighttime Maximum RH < 31%	W	W	W	W

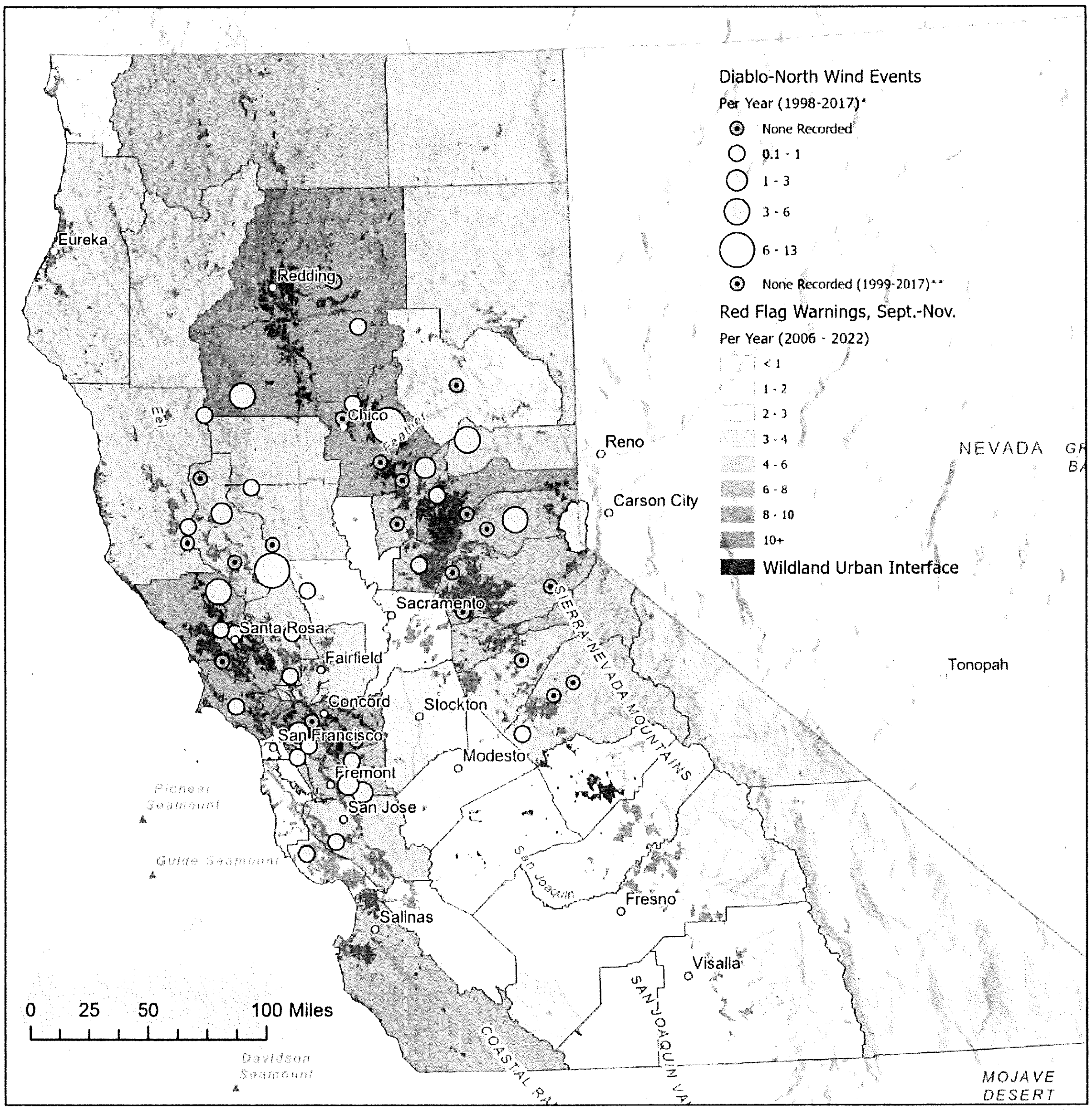
Source: National Interagency Fire Center:
https://gacc.nifc.gov/oscc/predictive/weather/myfiles/Watches_and_Warnings_for_California.htm

Figure 9 displays a map showing the number of DNW events per year by weather station location in the McClung and Mass (2020) study as well as the stations where Smith et al. (2018) found no recorded events. Also shown are the number of RFWs issued for each county in the months of September through November by the National Weather Service. The RFWs for a county are counted only when the warning area intersects a Wildland Urban Interface (WUI) area within the county. DNW events mapped by McClung and Mass (2020) tend to occur in counties with higher incidence of Red Flag Warnings. Only one North Wind event was recorded by McClung in the Central Sierra counties south of Lake Tahoe. RFWs also decline in number in the Sierras to the south of Lake Tahoe.

McClung and Mass (2020) found no evidence that DNW events are increasing over time. Mass et al. (2019) suggested that the pressure gradient that produces these winds may actually decrease in the future as interior regions warm. A decrease in the number of wind events, however, could be offset by the lengthening of the dry season as climate warms. That could result in an increasing number of the fall wind events that coincide with dry conditions conducive to fire spread. (Williams et al., 2019).

The institution of power shutoffs by utilities when wind events are forecast during the fire season, a practice that began in 2019, has the potential to reduce the number of fires that occur during high winds. Five of the six wind-dominated fires described in Keeley et al. (2018) were caused by powerline failures, including the Tubbs Fire and the Camp Fire. Pacific Gas & Electric estimates that its five planned power shutoffs in 2021 reduced acres burned in wildfires by as much as 700,000 acres, based on the wind damage to equipment that occurred during those shutoffs (PG&E, 2022).

Figure 9: Diablo-North Wind Events and Red Flag Warnings



*(Sources: *McClung and Mass, 2020; **Smith, 2018; Red Flag Warnings: Iowa State University Environmental Mesonet; WUI: Silvis Lab, 2022).*

5. Discussion

If only estimates of vegetation cover near homes and housing density are included, the logistic model for moderate wind fires is a poor predictor of structure loss, with an AUC of 0.569. The initial model for DNW fires is a more accurate, with an AUC of 0.702, but that still barely qualifies as acceptable. Adding an autocovariate that reflects the fate of neighboring houses substantially improves the prediction accuracy of both models while addressing the issue of spatial autocorrelation. The AUC increases to 0.870 for the moderate wind model and to 0.885 for the DNW model. Those improvements demonstrate that the outcomes for neighboring houses during a fire have a large impact on structure loss rates, as noted by Knapp et al. (2021) for the Camp Fire.

The autocovariate helps to account for situations where, based on pre-fire conditions, groups of homes unexpectedly survive (as in the Coffee Park example) and when they do not. If winds die down or change direction, groups of houses that have high levels of vegetation cover or housing density may avoid destruction. Successful defensive efforts could also lead to survival of housing clusters that would otherwise be lost. Conversely, temporary increases in fire intensity and ember showers due to gusting winds could raise loss rates for groups of homes that are exposed at that moment, despite having lower levels of vegetation cover or housing density. The ignition of a nearby house can also increase the risk of loss. The housing density variable captures some of the risk of house-to-house fire spread, but the autocovariate provides additional information - whether or not nearby houses have burned.

The autocovariate has a larger impact on classification accuracy for moderate wind fires compared to DNW fires. That could be a product of the greater variability in fire behavior during moderate wind fires. In the three DNW fires, almost all structure losses took place within a single 12-hour period, characterized by sustained high winds. In moderate wind fires, which can take place over days or weeks, wind speeds may vary greatly from hour to hour and from day to day. The outcome for neighboring houses, as measured by the autocovariate, captures some of that variability.

Housing density does not seem to have a strong influence on loss rates in moderate wind fires. Predicted loss rates are similar across all housing density classes for a given vegetation cover level. (Table 8). Lack of structure-to-structure spread in lower winds could be one explanation. Effective defensive efforts could be another reason. The lower rate of fire spread in moderate wind fires allows more time for fire-fighting resources to be deployed and for those resources to be concentrated on fewer houses at any one time. Fire fighters may also target higher density neighborhoods for protection because that is where the risk of loss is greatest.

In DNW fires housing density has a much greater impact on losses. Estimated loss rates for DNW fires at high housing densities are 25-35% above loss rates for low housing densities with equivalent vegetation cover. At housing densities of 2.0 per acre, predicted loss rates top 84% even at low levels of vegetation cover (Figure 5 and Table 8). According to Maranghides et al. (2022) structure-to-structure spread predominates and parcel-level vegetation management is largely ineffective when housing densities exceed 2.0 per acre. The speed of spread in DNW fires likely contributes to the high loss rates in dense communities. The simultaneous ignition of many homes means that fire fighters are unable to respond to most structure ignitions and have limited effect on losses (Calkin et al., 2014).

Changes in vegetation cover have a modest effect on loss rates in both moderate wind and DNW fires. In moderate wind fires, a 10% change in vegetation cover within 50 meters results in about a 4% change in loss rates (Table 9). For DNW fires, a 10% change in vegetation cover yields a 6.5% change in loss rates when housing density and vegetation cover are low, but only a 1.4% change when housing density and vegetation cover are high. Excluding areas of high housing density, these impacts are similar to the 5% average response found by Gibbons et al. (2012) for a 10% change in vegetation cover within 40 meters.

A low level of vegetation cover near homes reduces but does not eliminate the risk of loss. A 20% vegetation cover still results in an estimated loss rate of 30% in moderate wind fires and 50% or higher in DNW fires. Additional measures such as removing ignitable materials within 1.5 meters of a structure and structure hardening to prevent ember ignition are required to achieve lower loss rates (Cohen, 2019). When high winds combine with high structure density, community-wide structure hardening is needed to prevent extensive losses from structure-to-structure fire spread (Maranghides et al., 2022).

High wind levels have a large impact on loss rates. Estimated loss rates for DNW fires are 20% to 60% higher than for moderate wind fires with the same level of vegetation cover and housing density (Table 8). Based on McClung and Mass (2020), homes in the San Francisco Bay Area appear to be at the highest risk for DNW events while homes in the Northern Sierras have about half the risk of those in the Bay Area. Red Flag Warning data support the suggestion by Ruscha (1976) that Mono Winds south of Lake Tahoe are less frequent than North Winds due to the blocking effect of the High Sierras. When DNW events do occur, pro-active power shutdowns have the potential to significantly reduce the risk of fire starts, helping to counteract the effects of a fire season that is stretching farther into the windy fall months.

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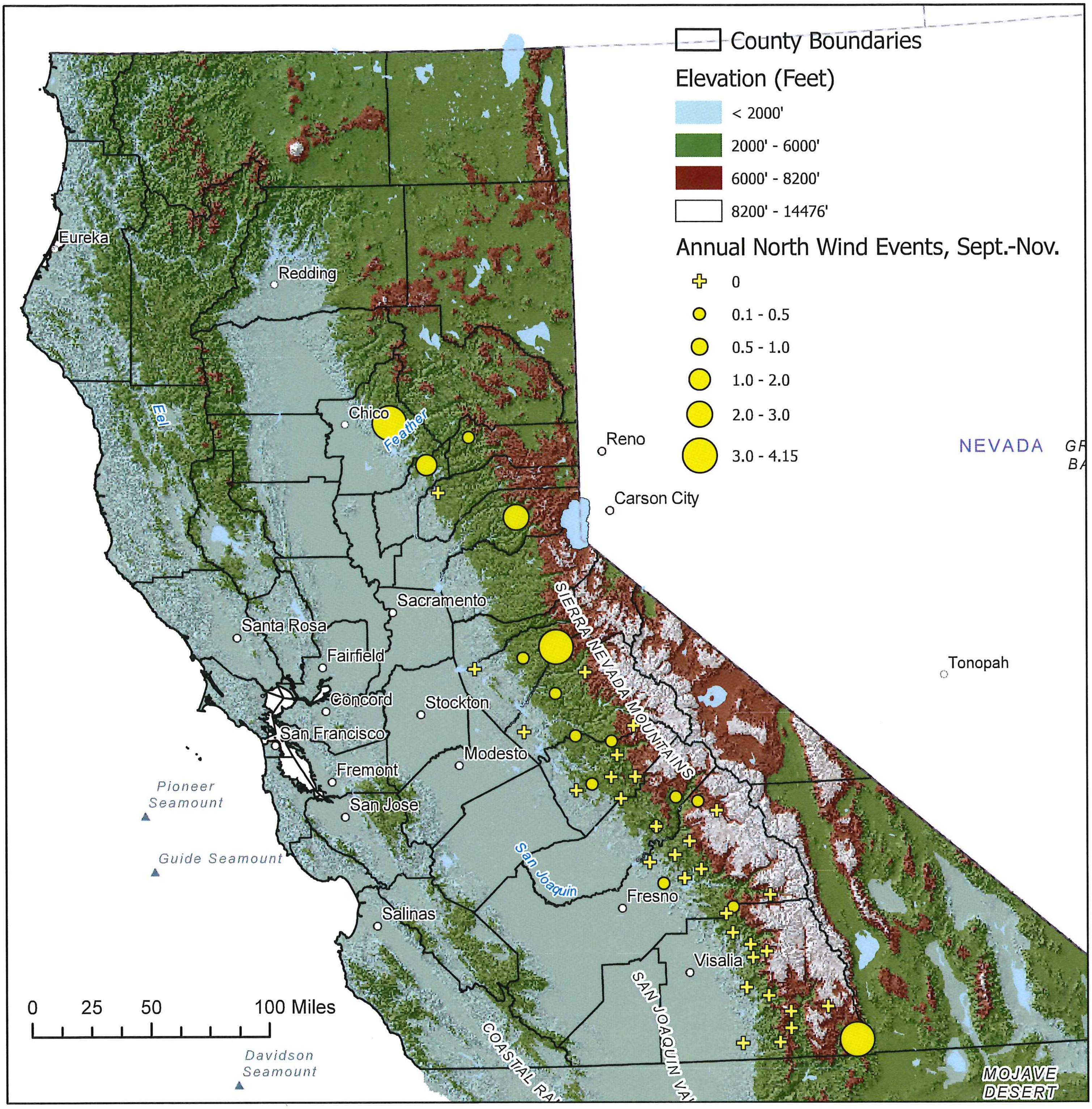

County Boundaries
Elevation (Feet)
< 2000'
2000' - 6000'
6000' - 8200'
8200' - 14476'
Annual North Wind Events, Sept.-Nov.
0
0.1 - 0.5
0.5 - 1.0
1.0 - 2.0
2.0 - 3.0
3.0 - 4.15
Eureka
Redding
Chico
Feather
Eel
Reno
Carson City
NEVADA
Tonopah
Sacramento
Santa Rosa
Fairfield
Concord
Stockton
San Francisco
Modesto
Fremont
San Jose
Pioneer Seamount
Guide Seamount
San Joaquin
Fresno
Salinas
Visalia
SIERRA NEVADA MOUNTAINS
0 25 50 100 Miles
Davidson Seamount
MOJAVE DESERT