

Modeling of multi-strata forest fire severity using Landsat TM Data

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ABSTRACT

Most of fire severity studies use field measures of composite burn index (CBI) to represent forest fire severity and fit the relationships between CBI and Landsat imagery derived differenced normalized burn ratio (dNBR) to predict and map fire severity at unsampled locations. However, less attention has been paid on the multi-strata forest fire severity, which represents fire activities and ecological responses at different forest layers. In this study, using field measured fire severity across five forest strata of dominant tree, intermediate-sized tree, shrub, herb, substrate layers, and the aggregated measure of CBI as response variables, we fit statistical models with predictors of Landsat TM bands, Landsat derived NBR or dNBR, image differencing, and image ratioing data. We model multi-strata forest fire in the historical recorded largest wildfire in California, the Big Sur Basin Complex fire. We explore the potential contributions of the post-fire Landsat bands, image differencing, image ratioing to fire severity modeling and compare with the widely used NBR and dNBR. Models using combinations of post-fire Landsat bands perform much better than NBR, dNBR, image differencing, and image ratioing. We predict and map multi-strata forest fire severity across the whole Big Sur fire areas, and find that the overall measure CBI is not optimal to represent multi-strata forest fire severity.

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1. Introduction

Landscape heterogeneity can change fire severity that often is classified into lightly burned, medium burned, and high burned patches (Hall et al., 1980; Van Wagner, 1983; Turner and Romme, 1994). Fire severity is associated with abiotic factors including weather, moisture, slope, and elevation (Romme and Knight, 1981; Christensen et al., 1989) and biotic circumstances, such as forest layers, stand structure, tree size, successional stage, pathogens, disease, mortality (Turner et al., 1999), and anthropogenic factors such as widespread logging, livestock, and urban development. On the other hand, large area fires could change landscape heterogeneity, ecosystem structure and local climate. Regional forest fire can have significant negative impacts on wildlife habitats and browsing (Romme and Knight, 1981). Forest fire often results in huge biomass and carbon loss, which may change local weather and climate. High soil burning leads to much more soil runoff and erosion compared with unburned and light burned areas (Robichaud et al., 2007). To understand the complex relationships between wildfire and forest ecosystems, we need to model multi-strata forest fire severity,

which has not been explored. Compared to one overall estimate of composite burn severity (CBI), modeling and mapping of fire severity across forest strata (i.e., substrate layer, herb layer, shrub layer, intermediate-sized tree, and dominant tree) can provide deeper insight information for fire severity, interactions between fire and vegetation, and vegetation resilience analyses.

Fire severity is difficult to measure and quantify. Key and Benson (2006) indicated that “no common standard” exists. The choices of fire related variables and the rates of fire severity with quantitative or qualitative estimates are typically determined by management, ecological purposes, and field sampling designs (Ryan and Noste, 1985). If fieldwork extends from several weeks to several months, environmental factors, such as rain or wind, could affect fire severity measurements.

Fire severity analysis has been improved by using normalized burn ratio (NBR) of Landsat band 4 and band 7 in comparing to the initial method for detecting fire severity that were based on normalized difference vegetation index (NDVI), which is derived from post-fire Landsat Thematic Mapper (TM) or Enhanced Thematic Mapper Plus (ETM+) (Diaz-Delgado et al., 2003; White et al., 1996). Recently, multispectral satellite remote sensing derived suitable indices for fire severity detection were compared and explored (Norton et al., 2009; Veraverbeke et al., 2010). Landsat data are widely used to calculate a radiometric index of NBR (Key and Benson, 2006). Multi-temporal differencing was used to enhance the contrast and changes from pre- and post-fire Landsat TM or

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ETM+ bands 4 (0.75–0.90 μm) and 7 (2.09–2.35 μm), and band 4 is sensitive to the chlorophyll amount of leafy vegetation and band 7 is suitable for detecting moisture contents in both vegetation and soils. The difference between pre-fire and post-fire NBR (dNBR) is the widely used method for fire severity mapping. The dNBR is often assessed using an overall field measure of fire severity CBI. This approach rates fire severity in all the layers of a forest stand and results in an aggregated value CBI, which can be compatible with satellite imagery derived dNBR (Cocke et al., 2005).

The potential disadvantages of CBI, NBR, and dNBR are critical and were explored by Epting et al. (2005), Keeley (2009), Lentile et al. (2006), Robichaud et al. (2007), and Roy et al. (2006). For example, (1) Pearson correlation coefficients between dNBR and field CBI are 0.0253, 0.0968, 0.3794, 0.5303 and 0.5379 respectively for conifer woodlands, mixed forests, closed conifer forests, open conifer forests, and hardwood forests (Roy et al., 2006); and dNBR can be weak for modeling of large area fire severity due to heterogeneous forest landscapes. (2) There is not a common rule to group dNBR into fire severity classes, which are prone to be subjective. (3) The dNBR can be a bad predictor of ecosystem responses even when dNBR and CBI are highly correlated, since CBI is an aggregated overall measure of fire severity metrics and ecosystem responses including resprouting of different vegetation layers cannot be identified respectively. And (4) dNBR is not optimal in describing fire severity shortly after fire, because most spectral changes are almost parallel between the near-infrared and middle infrared and thus dNBR is not sensitive to fire-resulted changes (Roy et al., 2006).

Fire severity studies often use Landsat data derived NBR and dNBR, but the information provided by the original bands somehow is overlooked in fire severity detection. The comparison of fire severity detection between NBR, dNBR, the combination of Landsat bands, Landsat image differencing, and image ratioing needs to be evaluated to understand the potential contribution of Landsat data to fire severity analysis. It is important to make a comprehensive study of fire severity modeling of multi-strata forests in order to understand fire activities and vegetation responses in different forest layers, although the dNBR calculated from remote sensing data was used to represent CBI.

In this study, we disintegrated the composite burn index into fire severity matrix of five forest strata substrate soils, understory herb, understory shrub, intermediate-sized tree, and dominant tree; we designed multi-strata forest fire severity modeling in order to make comprehensive understanding of fire severity among different forest strata, identify responses of different forest strata to fire behaviors, and explore Landsat data derived different fire severity modeling and prediction across the five forest strata. In the process of fire severity modeling, we aimed to find whether Landsat data derived NBR and dNBR are superior to its bands, image differencing and ratioing for fire severity detection. We fitted the fire severity models using NBR, dNBR, combinations of Landsat TM bands, and Landsat image differencing and ratioing and then assessed the differences among these models. We mapped multi-strata forest fire severity using Landsat TM data as predictors, which provided much more fire severity information than other types of predictors of NBR, dNBR, band differencing and ratioing. This study was ended with a concise discussion and summarization of potential applications of Landsat remote sensing for fire severity modeling.

2. Study area

Big Sur coastal ecoregion, the 90 miles (145 km) of coastline between the Carmel River and SanCarpoforo Creek, is highly marked by steep creeks and easily erodible drainages with significant changes of elevations from sea level to 1571 m (Fig. 1). Big Sur is a typical region that symbolizes the Mediterranean-type climate and

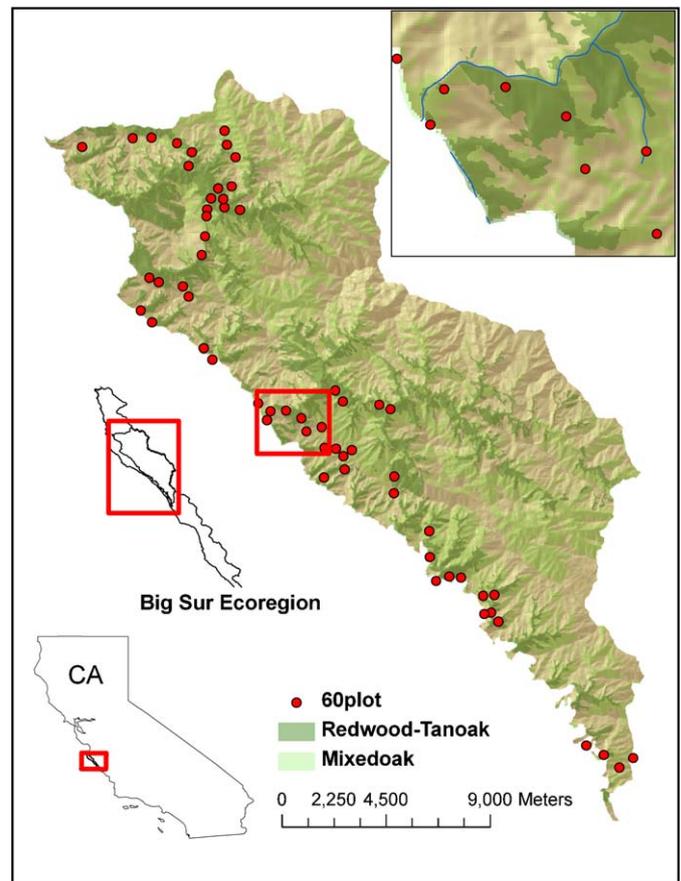


Fig. 1. Big Sur complex fire area, California, USA.

is characterized by warm to hot, dry summers but cool and wet winters. The recorded minimum temperature in December is -2.8°C and the maximum temperature in June is 38°C . The annual precipitation is often within the range between 1065 mm and 515 mm; that decreases from north to south, and more than 70% rainfalls occur from December through March. The dry and wet seasons, which are usually for describing tropics, are a significant characteristic within Big Sur ecoregion. The wet season is usually from November 1st to April 30th, and the dry season is from May 1st to October 30th. However, it is difficult to generalize more detailed climate characteristics within Big Sur, because highly heterogeneous changes in topography and landscape that causes different and separated microclimates. These complex Mediterranean-type climates provide optimal habitats for complex ecosystem and heterogeneous vegetation communities (Henson and Usner, 1996).

The Big Sur Basin Complex (BSBC) fire started on June 21, 2008 and was declared at 6:00 P.M. on July 27, 2008 (KUSP, 2008). This fire, being the historical recorded largest wildfire in California, resulted in a total burned area 95,000 ha with centroids of latitude and longitude (36.26, -121.72) (Fig. 1).

We analyzed fire severity in the two dominant forests mixed oak and redwood-tanoak forests (*Sequoia sempervirens*–*Lithocarpus densiflorus*), which are the primary habitats for *P. ramorum* (a type of mold) in this region (Maloney et al., 2005). Numerous oak trees died due to *Phytophthora ramorum*, which is usually called sudden oak death. Meentemeyer et al. (2008) mapped these two dominant forest types in this study region to understand the potential distribution of the sudden oak death disease. Mixed oak forests consisting of coast live oak, Shreve's oak, bay laurel (*Umbellularia californica*), and madrone (*Arbutus menziesii*) grow on moister slopes. At further lower elevations are redwood-tanoak forests, but

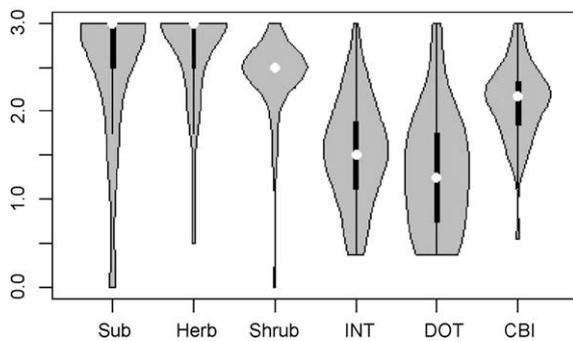


Fig. 2. Kernel density distribution of field measurements of fire severity (0–3): CBI, composite burn index; DOT, dominant tree layer; INT, intermediate-sized tree layer; Shrub, shrub layer; Herb, herb layer; and Sub, substrate layer.

some deciduous coastal sage scrub vegetation also lives at relatively low elevation south- and west-facing slopes, where are typically drought vegetation habitats.

3. Methods

3.1. Field survey

The University of California at Davis and the University of North Carolina at Charlotte established and surveyed ninety-seven 500 m² (e.g., 25 m diameter) plots within the BSBC fire perimeter in fall, 2007. All the plots were created randomly across two dominant forests redwood-tanoak and mixed oak belonging to California State Parks, US Forest Service, and private landowners. A trained group used differential GPS to measure positions of plot centroids and surveyed and recorded pre-fire attributes including forest health status, tree size, species, and density of all the trees and shrubs. The attributes of herbs and soils within the plots were quantified and recorded too. After the BSBC fire, 60 among the total 97 plots were surveyed again from September 2, 2008 to October 29, 2008 (Fig. 1), since a large winter storm occurred on October 30, 2008 and our field fire severity survey stopped.

Fire severity of the five forest layers (i.e., substrate soils, herb, shrub, intermediate-sized tree, and dominant tree) were quantified and a score (0–3) of fire severity of each strata layer within a plot was recorded. According to pre- and post-fire attributes of each forest layer, changes of coarse woody debris, soil, duff, and leaf litter due to fire were considered as the main evaluation to quantify the score of fire severity of substrate layer. Changes and responses of any vegetation less than 1 m height were applied to assess and quantify the score of fire severity within herb layer. Any changes of vegetation higher than 1 m but less than 5 m were used to measure the score of fire severity of shrub layer. Trees higher than 5 m but standing under the dominant canopy experienced fire were considered for fire severity of intermediate-sized tree layer. Dominant trees were used to evaluate fire severity of dominant tree layer. The overall rate of CBI was assessed using the average of the scores of fire severity across the vertical five forest strata layers.

Multi-strata forest fire severity was measured across each whole plot and a basic kernel distribution of the field fire severity was portrayed in Fig. 2. The inner box plot indicated the median, the first quartile, and the third quartile of fire severity and the out density trace indicated the detailed changes of distribution. Fire severity of substrate and herb layers with median 3 was extremely left skewed. Fire severity of shrub layer and the overall burn index (i.e., CBI) with median respectively 2.5 and 2.1 was little skewed to the left. Fire severity of intermediate-sized tree and dominant tree layers with median 1.6 and 1.3 respectively was skewed to the right.

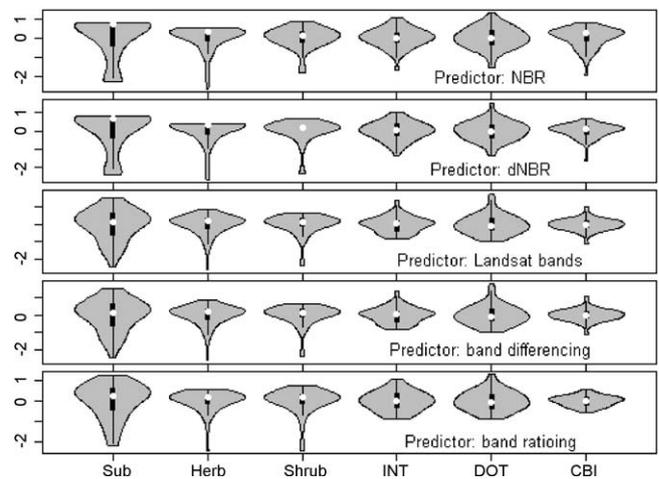


Fig. 3. Kernel density distribution of model errors of forest strata fire severity using predictors NBR, dNBR, Landsat TM bands, Landsat TM differencing and ratioing.

Fire severity in this paper was a continuous score from 0 to 3 of the landscape changes including trees, shrubs, herbs, and soils. It was quantified based on pre-fire and after-fire conditions. CBI was used as an overall assessment of fire severity within a plot and it was an aggregated fire severity score based on multiple assessments of different forest layers in terms of fire actions and ecosystem responses. These assessments included the charring of substrate materials, scorch height, the amount of changed and unaltered vegetation, and the degree of vegetation regeneration.

3.2. Landsat data

The cloud free pre-fire Landsat TM scene August 15, 2007 and post-fire scene October 20, 2008 at level 1G were ordered from US Geologic Survey, Earth Resources Observation and Science Center (EROS). The images were computed to at-satellite reflectance. The NBR was computed for each scene as Eq. (1). The dNBR was then computed using pre-fire NBR (i.e., NBR_{pre}) minus the post-fire NBR (i.e., NBR_{post}) (Eq. (2)). We were interested in the differences of post-fire NBR and dNBR for fire severity analysis, and both of them used as predictors for fire severity modeling.

$$NBR_{TM} = 1000 \left[\frac{(\text{Band}_4 - \text{Band}_7)}{(\text{Band}_4 + \text{Band}_7)} \right] \quad (1)$$

$$dNBR_{TM} = NBR_{pre} - NBR_{post} \quad (2)$$

Image differencing produces a new change image through the subtraction of pixel by pixel between two dates' data (e.g., Muchoney and Haack, 1994), and it is often applied to land cover change analysis. We obtained the differencing images using the pre-fire Landsat TM bands to minus the post-fire Landsat TM bands respectively; for example, differencing of band 1 is equivalent to the digital number of pre-fire Landsat TM band 1 minus the digital number of post-fire Landsat TM band 1. Another typical approach of change detection is image ratioing that results in a new image with ratios of pixel to pixel in each band (e.g., Nelson, 1983). The Landsat TM ratioing data were processed using the pre-fire Landsat TM bands divided by post-fire Landsat TM bands respectively; for instance, ratioing of band 1 is equivalent to the digital number of pre-fire Landsat TM band 1 divided by the digital number of post-fire Landsat TM band 1. Post-fire Landsat TM bands (1, 2, 3, 4, 5, 6, and 7), post-fire NBR, dNBR, image differencing, and image ratioing data were applied as predictor variables to make separately modeling of multi-strata forest fire severity analysis (Table 1).

Table 1
Fitted models using different Landsat TM data.

Responses	Predictors		Landsat TM bands	Differencing of bands	Ratioing of bands
	NBR	dNBR			
Fire severity					
Substrate	$Y = 0.02 + 0.000076 \times \text{NBR}$	$Y = 2.1835 + 0.00353 \times \text{dNBR}$	$Y = 2.450 - 2.0528 \times b4 + 9.5638 \times b5 - 9.338 \times b7$	$Y = 1.4405 + 0.1838 \times b1d - 0.15765 \times b3d - 0.0573 \times b6d$	$Y = 6.8408 + 7.2248 \times b1r - 3.3876 \times b3r + 0.8826 \times b5r - 9.7868 \times b6r$ $Y = 1.3178 + 1.5301 \times b2r - 0.54 \times b7r$
Herb	$Y = 2.5398 + 0.00032 \times \text{NBR}$	$Y = 2.6254 + 0.000176 \times \text{dNBR}$	$Y = 2.968 - 2.703 \times b2 + 3.724 \times b5 - 2.789 \times b7$	$Y = 2.1077 + 0.014342 \times b4d$	
Shrub	$Y = 2.0877 + 0.00057 \times \text{NBR}$	$Y = 2.2589 + 0.000226 \times \text{dNBR}$	$Y = 2.9968 - 4.0544 \times b2 + 4.0027 \times b3 - 0.7824 \times b6$	$Y = 2.3551 - 0.50 \times b3d + 0.02545 \times b5d$	$Y = 3.7438 - 1.9385 \times b3r + 0.664 \times b5r$
Intermediate-sized tree	$Y = 2.0896 - 0.00146 \times \text{NBR}$	$Y = 1.1002 + 0.001978 \times \text{dNBR}$	$Y = 1.8505 - 5.4936 \times b2 + 4.6312 \times b3$	$Y = 0.9874 - 0.390 \times b1d - 0.0472 \times b3d + 0.0898 \times b5d - 0.1125 \times b7d$	$Y = 1.4702 + 0.3816b4r - 0.5942 \times b7r$
Dominant tree	$Y = 1.9389 - 0.00177 \times \text{NBR}$	$Y = 0.7061 + 0.00255 \times \text{dNBR}$	$Y = 1.7813 - 6.4865 \times b2 + 5.8124 \times b3 - 0.5209 \times b4$	$Y = 0.694454 + 0.023288 \times b4d - 0.031290 \times b6d$	$Y = -2.0017 + 2.6414 \times b1r + 0.4809 \times b4r - 0.887 \times b7r$
Composite burn index	$Y = 2.3301 - 0.00067 \times \text{NBR}$	$Y = 1.8064 + 0.001223 \times \text{dNBR}$	$Y = 2.4835 - 3.4739 \times b2 + 2.1485 \times b3 - 0.6432 \times b4 + 2.595 \times b5 - 2.1048 \times b7$	$Y = 1.65326 - 0.0584 \times b3d + 0.05053 \times b5d - 0.0625 \times b7d$	$Y = 1.92486 + 0.98519 \times b3r + 0.1771 \times b4r - 5429 \times b7r$

Note: NBR, normalized burn ratio; dNBR, differenced normalized burn ratio; b1, Landsat TM band 1, 2, 3, 4, 5, 6, and 7; b1r, b2r, b3r, b4r, b5r, b6r, and b7r, ratioing of Landsat TM band 1, 2, 3, 4, 5, 6, and 7.

3.3. Regression modeling

We first made a data exploration, and a typical linear trend of the relationships between multi-strata fire severity and Landsat TM data existed. Linear regression was used to fit the relationships between post-fire Landsat TM bands, NBR, dNBR, image differencing, image ratioing data and the field measurements of multi-strata forest fire severity (Table 1). A stepwise multiple linear regression was used to select the significant bands of post-fire Landsat TM data; similar modeling process was applied to image differencing and image ratioing. The selected significant bands were then used as predictors to fit fire severity models for each strata layer and predict multi-strata forest fire severity at unsampled locations.

Statistical tests and leave-one-out cross validation were used for model diagnostics. *F*-statistics was used to test the significance of *R*-squared and the significance of the regression model as a whole. Adjusted *R*-squared was used to summarize the basic model performance. We used leave-one-out cross validation to assess model prediction of multi-strata forest fire severity with different predictor variables of dNBR, NBR, Landsat bands, image differencing, and image ratioing data. Using the linear regression with dNBR as base model, we computed Bayes factor to compare all the regression models and select a better model for multi-strata forest fire mapping. Bayes factor is a robust statistical criterion for model performance comparisons without considering the prerequisite that models should have the same dependent variables and the same samples are used. Regarding model comparisons using Bayes factor (BF), we typically have the different scenarios below: negative evidence for model 1 against model 2 if $BF < 0$, an evidence for model 1 against model 2 not worth more than a bare mention if BF is between 0 and 2.2, positive evidence if BF is between 2.2 and 6, strong evidence if BF is (6, 10), and very strong evidence if BF is larger than 10 (Raftery, 1996).

4. Results

We fitted 30 linear models of fire severity (e.g., across five forest strata plus CBI) using five types of predictors (NBR, dNBR, Landsat TM bands, image differencing, and image ratioing (Table 2)). Very weak relationships were found between fire severity and the NBR and dNBR for substrate, herb, and shrub layers (*R*-squared less than 0.1); strong positive relationships for the intermediate-sized tree and dominant tree layers. As for the overall fire severity (e.g., CBI), moderate relationship was found between NBR and fire severity, and there was relatively strong positive relationship in the model using dNBR as predictor (Table 2).

Could the post-fire original bands provide useful information for fire severity modeling as the index of NBR or dNBR? All the post-fire Landsat bands were used to fit the classic linear regression models with multi-strata forest fire severity as the response variable. The significant band combinations for fire severity of each forest layer were selected. The relationship between Landsat TM bands 457 and fire severity of substrate layer was relatively weak. There were strong relationships between Landsat TM bands 257, 236, 23, and 3457 and fire severity of herb, shrub, intermediate-sized tree, and CBI respectively. Very strong relationship was found between Landsat TM bands 234 and fire severity of dominant tree layer (Table 2). We then applied the same procedure to Landsat derived image differencing and ratioing data and summarized the results in Table 2.

We compared the basic model performance using adjusted *R*², which is adjusted for the number of predictors in the model. The linear models using original Landsat bands as predictors resulted in higher values of adjusted *R*² and performed better than other

Table 2
Fire severity modeling with Landsat TM derived data.

	NBR		dNBR		TM bands [*]		Differencing		Ratioing	
	R ²	Adj R ²	R ²	Adj R ²	R ²	Adj R ²	R ²	Adj R ²	R ²	Adj R ²
Substrate	0.009	-0.019	0.006	-0.012	0.138	0.085	0.293	0.248	0.290	0.223
Herb	0.009	-0.01	0.005	-0.012	0.221	0.171	0.121	0.103	0.112	0.072
Shrub	0.03	0.011	0.003	-0.017	0.261	0.215	0.201	0.166	0.182	0.144
Intermediate-sized tree	0.246	0.231	0.274	0.259	0.398	0.374	0.398	0.347	0.271	0.237
Dominant tree	0.289	0.275	0.365	0.352	0.551	0.523	0.263	0.233	0.384	0.344
CBI	0.102	0.084	0.204	0.189	0.466	0.407	0.349	0.304	0.478	0.414

Note: Adj R², adjusted R-squared.

^{*} Bands are selected at significant level 0.05.

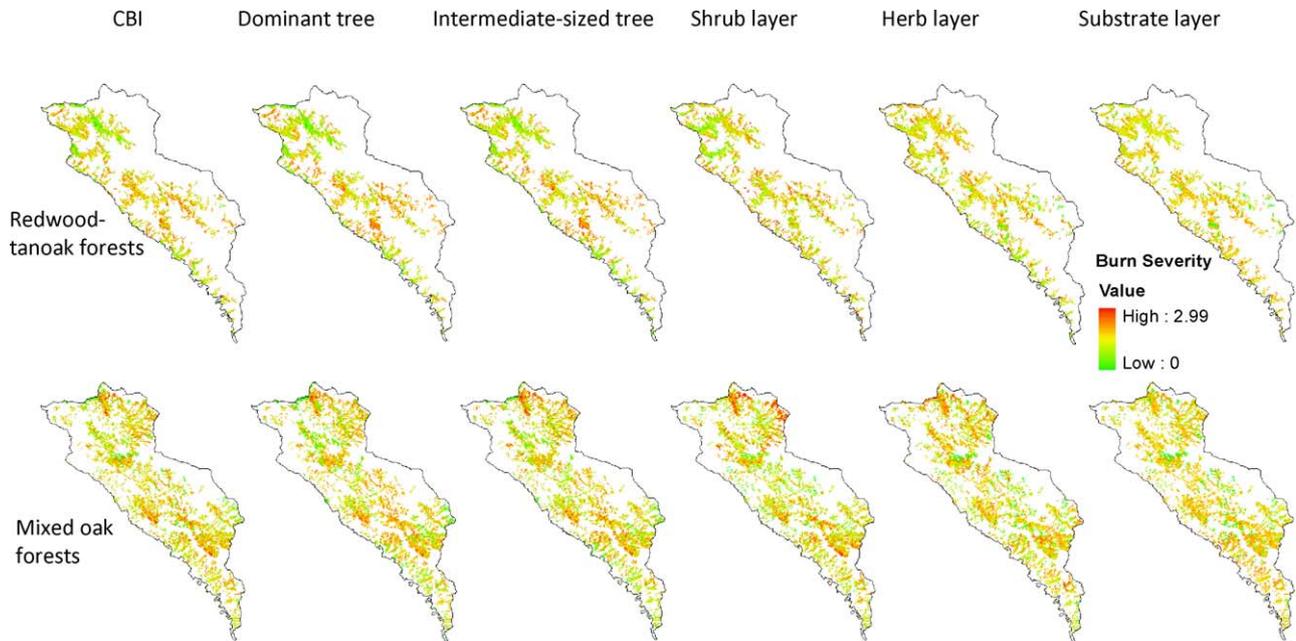


Fig. 4. Map composite burn index (CBI) and multi-strata fire severity of Big Sur Basin complex fire area.

models with predictors NBR, dNBR, image differencing, and image ratioing data for CBI and forest layers of herb, shrub, intermediate-sized tree, and dominant tree. Image differencing data resulted in relatively better results for substrate layer compared to other Landsat data.

Mean absolute error from leave-one-out cross validation was used to check error structure and validate model prediction (Fig. 3). The errors of the NBR and dNBR models typically resulted in much more high error values compared to the models using Landsat bands, band differencing, or band ratioing as predictors. The error differences among the models using Landsat TM bands, band differencing, and band ratioing were little, although it seemed that band ratioing model resulted in relatively higher error values for strata substrate, herb, and shrub layers. Using the linear regression model with dNBR as the base model, Bayes factor were applied to model performance diagnostics and the selection of the best predictive model (Table 3). Compared to the model using dNBR as predic-

tor, there was very strong evidence that the post-fire Landsat TM bands performed much better for overall CBI and the dominant tree layer, strong evidence that the post-fire TM bands performed better for intermediate-sized tree and shrub layers, and positive evidence that TM bands performed better herb layer modeling; there was not any significant evidence for substrate layer, while there was very strong evidence that image differencing model performed much better for substrate layer. Image differencing was used for fire severity prediction of substrate layer and Landsat TM bands were used as predictors to map fire severity CBI and other four types of forest layers (herb, shrub, intermediate-sized tree, and dominant tree layers) with cell size 25m across the BSBC fire area (Fig. 4).

We randomly sampled 300 locations across the predicted fire severity of redwood-tanoak and mixed oak forests respectively in order to understand the multi-strata fire severity. Fire severity in redwood-tanoak and mixed oak forests had similar distribu-

Table 3
Bayes factor for model selection using the dNBR model as the base model.

	dNBR	NBR	TM bands	Image differencing	Image ratioing
Substrate	-	0.12	-0.17	10.08	0.92
Herb	-	-0.40	4.57	6.21	-8.91
Shrub	-	-1.45	6.26	6.08	-6.72
Intermediate-sized tree	-	1.97	7.78	-0.15	-46.41
Dominant tree	-	5.86	16	-9.61	6.38
CBI	-	6.28	15.1	15.12	20.1

Table 4

F-statistics for fire severity modeling with Landsat TM images.

	NBR		dNBR		TM bands		Differencing		Ratioing	
	F	P-value	F	P-value	F	P-value	F	P-value	F	P-value
Substrate	0.010	0.922	0.126	0.724	2.571	0.065	5.694	0.006	3.662	0.018
Herb	0.475	0.494	0.087	0.770	4.529	0.007	6.381	0.014	2.856	0.046
Shrub	1.557	0.218	0.143	0.707	5.662	0.002	12.940	<0.0001	10.190	0.000
Intermediate-sized tree	16.310	0.000	18.870	<0.0001	16.210	<0.0001	3.375	0.041	3.618	0.034
Dominant tree	20.320	<0.0001	28.720	<0.0001	19.640	<0.0001	6.757	0.000	1.325	0.277
CBI	5.699	0.021	12.850	<0.0001	8.016	<0.0001	11.820	<0.0001	5.537	0.0004

tions, which were tested using a MANOVA (Multivariate Analysis of Variance) approach and displayed in Fig. 5A and B. The estimated medians of fire severity in redwood-tanoak forests were 1.92, 0.97, 1.22, 1.41, 2.48, and 2.33 respectively for CBI, dominant tree layer, intermediate-sized tree layer, shrub layer, herb layer and substrate layer. The estimated medians of fire severity were 1.96, 1.07, 1.29, 1.43, 2.51, and 2.36 respectively across the multi-strata mixed oak forests. The small *P*-value indicated fire severity distributions across multi-strata forests were significantly different; the CBI value was much higher than the fire severity in dominant tree, intermediate-sized tree, and shrub layers, and CBI could not represent fire severity of the forest layers of dominant trees, intermediate-sized trees, and shrubs.

5. Discussion

The *P*-value of *F*-statistics is the probability of rejecting the null hypothesis that the linear relationship is not significant. The smaller the *P*-value of the fitted linear models, the smaller the mean

absolute error from leave-one-out cross validation, the higher the confidence we had in fire severity prediction at unsampled locations. Landsat bands generally resulted in better model fitting than other models, but the *P*-value for substrate layer was above the significant level 0.05 (Table 4).

Compared to Landsat TM bands, image differencing, and image ratioing, dNBR or NBR did not show advantage for multi-strata forest fire severity detection. The combinations of Landsat bands provided more useful fire severity information than dNBR or NBR. As the disadvantages of dNBR discussed above, the correlation between dNBR and ground measurement of fire severity can be significantly changed due to heterogeneous topography and vegetation diversity and pattern composition. Additionally, the dNBR was not an optimal index describing fire severity shortly after-fire, because most spectral changes are almost parallel between the near-infrared and middle infrared (Roy et al., 2006).

Landsat TM band combinations had better fire severity modeling than the conventional approaches of NBR and dNBR. We would suggest applying post-fire Landsat TM bands to fire severity modeling rather than dNBR. However, comparison and validation of modeling with different predictors (e.g., band combinations, image differencing and ratioing, and dNBR) are worth doing in order to select a better model performance. Different TM band combinations need to be selected based on model diagnostics to avoid significant multicollinearity and potential overfitting. A high level of correlation among remote sensing data is quite common; Meng et al. (2009) showed multicollinearity exists in Landsat data, and for example, Pearson correlation coefficients were larger than 0.8. Significant collinearity among model predictor variables can inflate standard errors and result in model overfitting. An overfitted model often has poor predictive performances, since the effects of some predictors are potentially over-estimated while others are under-estimated, although multispectral bands and band indices often are combined and applied to predictions.

6. Conclusion

Fire severity across forest strata of dominant tree, intermediate-sized tree, shrub, herb and the overall measure CBI across heterogeneous landscapes were predicted and mapped using the best models with post-fire Landsat TM bands as predictors. Fire severity of substrate layer was predicted and mapped using the model with image differencing as predictor. Multi-strata forest burn severity has not got enough attention in current wildfire studies. Multi-strata forest fire analyses and mapping provide critical information for fire management and vegetation resilience studies. This study indicated that the differences of fire severity across multi-strata forest layers were significant, and CBI was not an optimal index to represent multi-strata fire severity. It is necessary to model multi-strata forest fire to understand vegetation resilience to fire and the complex relationships between fire and forest ecosystems.

Very strong relationships between fire severity of dominant trees and the combined bands were captured by Landsat TM data;

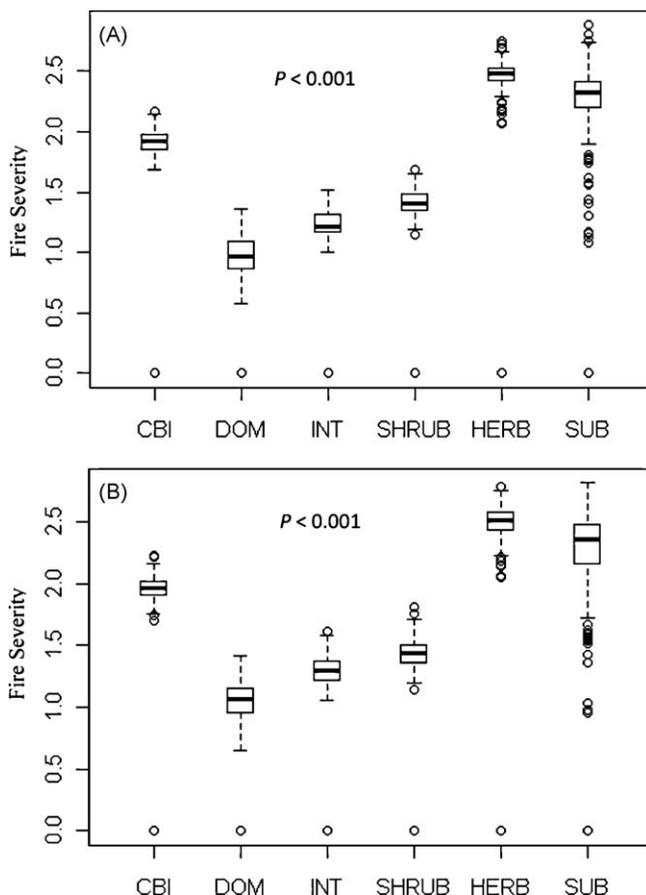


Fig. 5. Comparison of fire severity across multi-strata forests (A) redwood-tanoak forests; (B) mixed oak forests. Other notes as Fig. 2.

Likewise, the very strong relationships between the overall fire severity CBI and the band combination, the strong relationships between the combined bands and fire severity of forest layers intermediate-sized tree, shrub layer, and herb layer. Model diagnostics indicated that fire severity modeling with combinations of Landsat bands as predictors overall performed much better than other models especially those models using dNBR. Landsat image differencing and ratioing also obtained higher *R*-squared values for modeling of CBI and fire severity of forest strata substrate, herb, and shrub layers than the models fitted with NBR or dNBR. The overall diagnostics showed that the different Landsat band combinations can be an optimal approach for multi-strata forest fire severity modeling across heterogeneous landscapes. The band combination of 4, 5, and 7 was significant predictors for fire severity of substrate soils; the combination of 2, 5, and 7 was significant predictors of fire severity of herb layer; bands 2, 3, and 6 were significant predictors of fire severity of shrub layer; bands 2 and 3 were significant predictors of fire severity of intermediate-sized tree layer; bands 2, 3, and 4 were significant predictors of fire severity of dominant tree layer; and bands 2, 3, 4, 5, 7 were significant for the overall measure of fire severity (i.e., the composite burn index). The above analyses indicated that post-fire Landsat band combinations as predictors can perform better than just NBR or dNBR for fire severity.

We explored Landsat TM original bands, NBR, dNBR, image differencing, and image ratioing (e.g., other environmental or vegetation indices could be added to meet different research requirements) for multi-strata forest fire severity modeling and mapping. The NBR and dNBR are based on Landsat bands 4 and 7, and they cannot include other spectral information, such as band 2 or 3 also were important for fire severity modeling of different forest strata. Image differencing and ratioing have some drawbacks that can reduce the performance of the overall fit of fire severity models. For example, both image differencing and ratioing are sensitive to co-registration and mixed pixels that can cause equal differences/ratios but with different fire damages due to different forest types and/or strata composition.

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