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Forest fuel mapping and evaluation of LANDFIRE fuel maps in Boulder County, Colorado, USA

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ABSTRACT

A key challenge in modern wildfire mitigation and forest management is accurate mapping of forest fuels in order to determine spatial fire hazard, plan mitigation efforts, and manage active fires. This study quantified forest fuels of the montane zone of Boulder County, CO, USA in an effort to aid wildfire mitigation planning and provide a metric by which LANDFIRE national fuel maps may be compared. Using data from 196 randomly stratified field plots, pre-existing vegetation maps, and derived variables, predictive classification and regression tree models were created for four fuel parameters necessary for spatial fire simulation with FARSITE (surface fuel model, canopy bulk density, canopy base height, and stand height). These predictive models accounted for 56–62% of the variability in forest fuels and produced fuel maps that predicted 91.4% and 88.2% of the burned area of two historic fires simulated in the FARSITE model. Simulations of areas burned based on LANDFIRE national fuel maps were less accurate, burning 77.7% and 40.3% of the historic fire areas. Our results indicate that fuel mapping efforts that utilize local area information and biotic as well as abiotic predictors will more accurately simulate fire spread rates and reflect the inherent variability of forested environments than do current LANDFIRE data products.

1. Introduction

The coniferous forests of the western United States are inherently fire prone. Rapid and widespread exurban development into these fire-prone ecosystems (Radeloff et al., 2005; Theobald and Romme, 2007) has created significant fire risks to human settlements, which have been exacerbated by recent trends towards a warmer climate (Westerling et al., 2006). Furthermore, in some ecosystem types, fire exclusion has contributed to increased hazard of severe fires by allowing fuels to accumulate where previously frequent fires prevailed (Covington and Moore, 1994; Caprio and Swetnam, 1995). Although the role of fire exclusion in creating current fire hazards is much debated for particular ecosystems (Schoennagel et al., 2004; Baker et al., 2007), there is a consensus that fire risk is and will continue to be high in most forest ecosystems of the US West. Recent years (e.g. 2000 and 2002) of widespread, severe fires associated with extreme drought and large economic losses from these wildfires (NIFC 2004) have stimulated national and local policies to mitigate fire risk.

A key issue in wildfire management and mitigation is quantifying the fuel load and spatial arrangement of combustible material across these fire-prone landscapes. With accurate digital fuel maps, spatially explicit fire models such as Fire Area Simulator (FARSITE), FlamMap, and FS Pro (Finney, 1998; McDaniel, 2007) can simulate fires in order to evaluate and plan mitigation and suppression efforts or to support wildland fire use management strategies (Gouma and Chronopoulou-Sereli, 1998; Keane et al., 2001). Yet many natural resource agencies do not have adequate fuel maps, nor have they commonly collected fuel information during field inventories (Chuvieco and Congalton, 1989; Maselli et al., 1996; Keane et al., 2001; Reeves et al., 2006; McDaniel, 2007).

The most commonly used method for creating fuel maps is the indirect method in which vegetation cover maps (often created with remotely sensed data) are used to create 'crosswalks' to fuel characteristics (Keane et al., 2001; Reich et al., 2004; Stratton, 2006; Platt et al., 2006). These methods are problematic because fuels are not always correlated well with vegetation type and the fine-scale variability of fuels within each polygon of similar vegetation is not accurately reflected. Furthermore, surface fuels are often obscured by the forest canopy when remotely sensed data are used to map forest fuels (Elvidge, 1988; Riano et al., 2003; Reich et al., 2004; Rollins et al., 2004; Jia et al., 2006). Consequently, the presence of understory grasses, shrubs, and seedlings (which can increase the rate of fire spread and the incidence of crown fire)

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is commonly predicted under the assumption that light is the only limiting resource for understory development (Reinhardt and Crookston, 2003; Seli, personal communication, February 13, 2007). Thus, areas of high canopy closure are assumed to have little or no understory fuels, whereas areas of low canopy closure are assumed to have more understory fuels. In many cases, though, other biophysical factors such as soil moisture, slope, and aspect also have important influences on understory plant growth (Peet, 1981).

At a national level, the LANDFIRE fuel mapping effort aims to "integrate relational databases, remote sensing, systems ecology, gradient modeling, and landscape simulation to create consistent and comprehensive products that are standardized across the entire United States" (www.landfire.gov). LANDFIRE fuels maps are currently used by forest managers and fire planners to help prioritize fuel treatments and suppress fires, but these fuel maps have rarely been locally field checked nor have fire simulations employing these data layers been evaluated against actual fires, which are two of the objectives of the current study for the montane zone of Boulder County, CO.

The overall objectives of the current study are to (1) measure ground, surface, and canopy fuels from a representative sample of vegetation cover types and topographic settings in the montane zone, (2) create fuel maps for these areas by exploiting relationships of biotic and abiotic variables to on-the-ground fuel measurements, (3) validate the simulated wildfire spread rate and crown-fire activity of the resultant fuel maps with two recent fires in Boulder County, and (4) compare the results with similar simulations based on LANDFIRE fuel maps for the same areas.

2. Study area

The study area is the montane zone (sensu Marr, 1961; Kaufmann et al., 2006) of Boulder County, CO, USA which includes elevations from 1800 m to 3000 m, covers an area of 71,567 ha, and is located at approximately 105° west longitude and 40° north latitude (Fig. 1). The county is located in Colorado's Front Range where vegetation varies along environmental gradients of elevation and moisture (Peet, 1981). The lower montane zone extends from approximately 1800 m to 2500 m and is characterized by open park-like stands of ponderosa pine (*Pinus ponderosa*) and Rocky Mountain juniper (*Juniperus scopulorum*) at the plains-grassland ecotone to dense stands of ponderosa pine mixed with Douglas-fir (*Pseudotsuga menziesii*) in more mesic areas. In the upper montane zone, which extends from 2500 m to 3000 m, topographic position becomes increasingly important as dense stands of ponderosa pine and Douglas-fir are often found on north-facing slopes and more open ponderosa pine woodlands typically dominate south facing slopes. Aspen (*Populus tremuloides*), limber pine (*Pinus flexilis*) and lodgepole pine (*Pinus contorta*) often co-occur with Douglas-fir and ponderosa pine in the upper montane zone (Veblen and Donnegan, 2004).

Boulder County is located in the continental interior of the US and is predominantly on the eastern side of the continental divide.

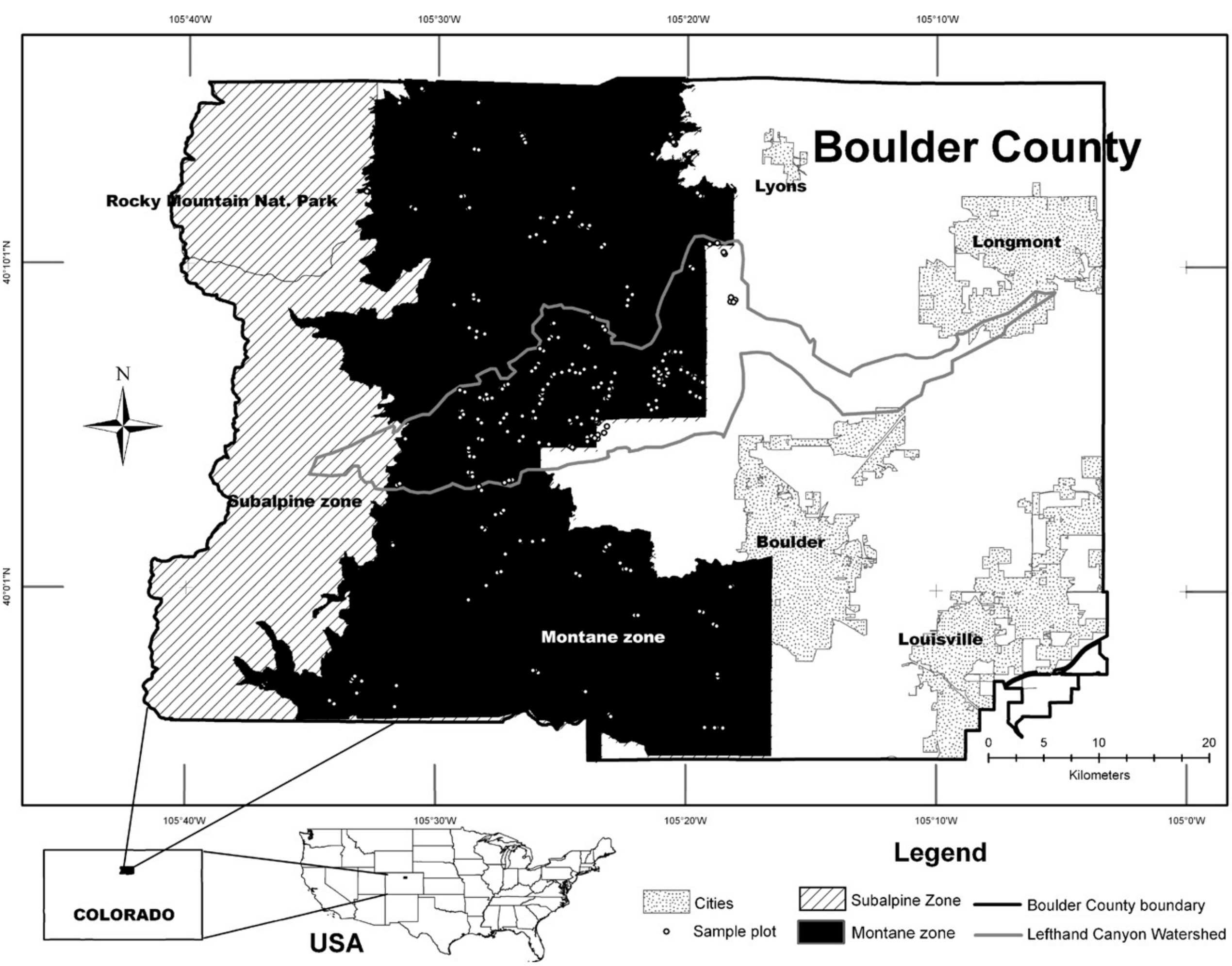

Fig. 1. Study area map. The montane zone is shown in black. Sample plots are shown as white circles, and the Lefthand Canyon Watershed is outlined in grey. The blank space to the west of the city of Boulder is forested land under the jurisdiction of Boulder Open Space Mountain Parks (and is not included in the IRI cover type map).

Its interior position results in relatively dry conditions and wide differences between winter and summer temperatures. Summer weather is typically hot and dry but with frequent afternoon thunderstorms. Wildfires can easily ignite during the fire season (June–September) from the combination of desiccated fuels, frequent lightning events, and anthropogenic ignitions (Veblen and Donnegan, 2004).

The study area is also punctuated with expansive exurban development as 27% of the county is considered part of the Wildland–Urban Interface (Radeloff et al., 2005). Land use in this area is heterogeneous as 40% of the land in the montane zone of Boulder County is managed by the US Forest Service, 28% is managed by the City of Boulder Open Space and Mountain Parks, 2% is managed by the BLM, and 30% is privately owned (Platt et al., 2006).

3. Methods

Fuel data from 196 study plots were used to build predictive classification and regression tree (CART, Brieman et al., 1984) models for each of four fuel parameters (surface fuel model, canopy bulk density, canopy base height, and canopy height). The models were then implemented in a GIS to create gridded fuel maps for the forested landscape in Boulder County. The resulting maps as well as the LANDFIRE national fuel maps for the same area were then used to simulate two actual fires in Boulder County using FARSITE (Finney, 1998).

3.1. Data acquisition

The Forest Service's Integrated Resource Inventory (IRI) dataset was used both for sample site selection and predictive modeling (USDA Forest Service, 1994). The Integrated Resource Inventory vector dataset was created in 1994 by a combination of photo interpretation of 1:24000 scale paper orthophotos and ancillary field data. The IRI layer delineates existing homogeneous units of vegetation of 5 or more acres (2 or more acres of wetland or riparian) over the entire montane zone of Boulder County. Polygons are homogeneous with respect to dominant tree species, crown, tree, shrub, forb, barren, and grass cover percentage.

In order to get representative and interspersed field data, sample plots (experimental units) were located in eighty vegetation polygons in the montane zone (1800–3000 m in elevation), which were randomly selected from the IRI dataset and stratified by forest type so that the proportion of sample plots in each forest type matched the proportion of that forest type in the larger study area. Forty percent of the sample plots were randomly located in Lefthand Canyon Watershed (approximately 14,000 ha) to serve as a more intensively sampled study area, while the other sixty percent of the plots were located in other montane locations throughout Boulder County (approximately 57,500 ha).

In the field, each randomly selected vegetation polygon was sampled with two to four randomly placed fuel inventory plots. The sampling goal was to capture the fine-scale heterogeneity of forest fuels within each vegetation polygon. The more heterogeneous polygons were sampled at three or four locations, whereas more homogenous polygons were sampled twice (hetero/homogeneity was determined from a combination of ground survey and aerial photo interpretation). Typical plots were $20\ \mathrm{m} \times 20\ \mathrm{m}$, though when tree densities were very high, smaller plots were sampled ($10\ \mathrm{m} \times 20\ \mathrm{m}$, or $10\ \mathrm{m} \times 10\ \mathrm{m}$) and on a few occasions when the tree density was very low, a larger plot was sampled ($20\ \mathrm{m} \times 30\ \mathrm{m}$, or $30\ \mathrm{m} \times 30\ \mathrm{m}$).

In each sample plot, ground and surface fuels were quantified with planar transects and duff and litter measurements on two perpendicular edges of the plot (Brown, 1974). A preliminary surface fuel model was assigned using the photo-series and surface fuel descriptions from Scott and Burgan's (2005) surface fuel models. Two digital photographs were also taken of areas that best exemplified the fuel complex in each plot. Surface fuel models were later verified or amended with the help of three fuel experts using plot data and photographs (see Section 3.2).

Canopy fuel characteristics were measured by a complete tree census within each plot. Tree species, tree height, diameter at breast height (dbh), canopy base height, crown ratio, and crown class were recorded for each tree above 4 cm dbh. Counts of seedling and saplings of each species were also recorded. Four measurements of canopy cover percentage were taken in each plot with a hand-held densitometer in a representative location in each plot. Slope, elevation, aspect, and UTM coordinates were also recorded in each plot. If the randomly placed plot landed in a site that had been previously logged, the plot was relocated to a nearby area without evidence of logging.

3.2. Data processing

Canopy bulk density, canopy base height, and canopy height were calculated from the tree data for each plot using the Forest Vegetation Simulator, Fire and Fuels Extension (FVS-FFE, Reinhardt and Crookston, 2003). Plot data were then examined for outliers or inconsistencies. In order to use the IRI canopy cover estimates for predictive modeling, it was necessary that the densitometer field measurements match the canopy cover estimates from the photo interpreted polygons. Therefore, any plots that had a discrepancy larger than 20% between the field measurement and IRI classification of canopy cover were excluded from the model building dataset (35 plots excluded—the original number of field plots was 231). A total of 196 field inventory plots were ultimately used to build predictive models.

Three fuel mapping and fire modeling experts familiar with the study area were consulted to refine the surface fuel model assignments. A wildfire and fuels specialist with the Arapahoe–Roosevelt National Forest, the fuels and fire behavior technical specialist for the Intermountain Regional Office of National Parks, and a member of the Fire Behavior Project at the USFS Fire Sciences Laboratory, Missoula, Montana all provided suggestions and feedback for assigning surface fuel models (personal communication, Stephen P., 28 November, 2006; Duran L., 20 November, 2006; Seli R., 13 February, 2007). Plot fuel data and photographs were used by the experts to determine the appropriate fuel models from the 40 Scott and Burgan (2005) surface fuel models.

As a result of the large number of surface fuel model choices for similar fuel types, as well as the newness of the Scott and Burgan (2005) 40 surface fuel models, minor discrepancies existed among the experts. Ultimately, assigning fuel models was an iterative process that involved making preliminary assignments from field data, creating a predictive model, implementing the model in a GIS and then validating the resulting surface fuel data layer by comparing the simulated fire behavior to historic fire events (the Walker Ranch and Overland Fires) using the Fire Area Simulator (FARSITE, Finney, 1998). Simulated spread rates and crown-fire activity were then used to inform the next iteration of the process until the simulated fire behavior matched historic fire events as closely as possible. This method for using expert opinion and validation to assign and fine-tune surface fuel models is the recommended procedure from the creators of the new surface fuel models as well as fire modeling experts at the Fire Science Laboratory and allowed for the creation of an accurate metric by which to compare LANDFIRE fuel maps (personal communication, Scott J., 8 March, 2006; Seli R., 13 February, 2007).

3.3. Model development and validation

Classification and regression trees explain the variance of a response variable by repeatedly partitioning the data into more homogenous groups (De'ath and Fabricius, 2000). This method was chosen to create predictive models in this study because it (1) accommodates both categorical and numeric variables, (2) allows non-linear relationships, (3) is robust with respect to outliers, and (4) has a simple graphical output that can be easily understood and interpreted (Brieman et al., 1984; De'ath and Fabricius, 2000; Reeves et al., 2006). One requirement of inferential statistics is that the observations be independent. In the case of this study, sample plots were the experimental units and were shown to be independent by determining the degree of spatial autocorrelation in ARC GIS by calculating Moran's I for each numerical fuel parameter (Moran, 1950). All fuel parameters showed no significant spatial autocorrelation between experimental units (using critical z-scores of -1.96 and 1.96), and thus each sample plot could be treated as an independent observation. Moran's I values (and z-scores) were as follows: canopy bulk density = 0.03 (1.03), canopy base height = 0.03 (1.01), and canopy height = 0.04 (1.19).

Separate predictive trees were developed for surface fuel model, canopy bulk density, canopy base height, and canopy height from field plots taken in the summer of 2006 (Fig. A1 in Supplemental Material). The fifth fuel parameter necessary for fire modeling, canopy cover, was already enumerated in the IRI dataset and was a useful predictor variable for the other four fuel parameters. Other predictor variables were either derived from a USGS digital elevation model (projected into UTM with a 30 m pixel size) or included in the IRI dataset, and included distance from streams, potential solar irradiance (McCune and Keon, 2002), slope, elevation, forest type (see Fig. A2), habitat structure (see Fig. A3), forb cover, shrub cover, barren cover, and grass cover (Table 1). Aspect is strongly related to potential solar radiation, but was also used as a separate predictive variable because it is uncertain which is more strongly correlated with vegetation patterns (Franklin, 1998). To create an index of 'northness,' aspect was transformed with a cosine function. These 12 variables were available across the entire study area and were used to predict the four unknown fuel parameters (surface fuel model, canopy bulk density, canopy base height, and canopy height) in each 30 m pixel of the resultant fuel maps.

Optimal CART models were determined for each fuel parameter by over-growing the predictive trees (20 leaves) and then pruning them back with a technique similar to the 1-standard error rule (Brieman et al., 1984; De'ath and Fabricius, 2000). This pruning method determined the smallest predictive tree for each fuel parameter such that its estimated error was within one standard deviation of the minimum error obtained by all possible trees for that fuel parameter (see Fig. A4). To estimate the error for each tree, 10-fold cross validation was performed 15 times on each classification and regression tree of every size. The cross-validated average misclassification rate was used for surface fuel model (categorical response variable), whereas the cross-validated average sum of squared errors (SSE) was used for canopy base height, canopy bulk density, and canopy height (numerical response variables) (Brieman et al., 1984; Venables and Ripley, 1997; De'ath and Fabricius, 2000; Miller and Franklin, 2002).

3.4. Model implementation

Each classification and regression tree was then implemented in ARC GIS 9.1 using the model builder interface to assign fuel values to each pixel of the study area according to the dichotomous progression of each predictive tree. Predictor variables in vector format were first converted to raster data layers in ARC GIS with 30 m^2 pixels. Separate raster grids were built for each of the four predicted fuel variables.

3.5. Fuel map validation

To validate the resulting fuel maps with pre-existing fires, they were clipped to the proper extent and converted into FARSITE landscape files using ARCFuels macros for ArcGIS 9.1 (Ager, 2005). The Overland Fire of 2003 and the Walker Ranch (Eldorado) fire of 2000 were both simulated in FARSITE (Finney, 1998). Ignition points, ground verified fire perimeters, fuel moistures, wind and weather information, as well as suppression activity for each fire were obtained from the Forest Service, the Boulder County Sheriff's office, Anchorpoint Fire Management Group, as well as a fire behavior analyst and fire fighters who worked on each fire (public communication, Pelle J., Overland Wildfire Sherriff's report, October 31, 2003; personal communication, Duran L., 20 November, 2006; personal communication, Moraga R. and White C. February, 20, 2007; unpublished data, Close K., Walker Ranch Fire Behavior Analyst report and files, accessed 21 February, 2007). Wind, weather, fuel moistures, burn periods, and suppression activities were modeled as closely to historical records as possible for each fire (Table 2). FARSITE adjustment factors were not employed in these simulations, nor were wind speeds or directions altered from those reported from the fire reports. The aim was to reproduce historical fire behavior with accurate fuels maps rather than by altering the FARSITE inputs, as is common practice to produce realistic fire behavior.

These two fire events are optimal for fuel layer validation because they were quite different in extent and burning behavior and also burned through a representative sample of fuel models and forest types for the montane zone of Boulder County. The Overland fire of October 29, 2003 was a one-day wind-driven event that burned 1566 ha in Lefthand Canyon, eight miles northwest of the city of Boulder. The Walker Ranch fire was a three-day, fuel and

Table 1
Predictor variable information (values rounded to nearest whole number, except aspect cosine transformed and potential solar radiation which are rounded to the nearest hundredth; GIS, geographic information system).

Predictor variable	Units	Data range	Mean	Standard deviation	Source	Assessment method
Aspect (cosine transformed)	Unit-less	2	.08	.77	Digital elevation model	Computed in GIS
Slope	Degrees	38	19	8	Digital elevation model	Computed in GIS
Forb cv.	Percent	15	3	4	IRI data	Field survey
Grass cv.	Percent	40	8	8	IRI data	Field survey
Barren cv.	Percent	51	19	9	IRI data	Aerial photograph interpretation
Shrub cv.	Percent	35	13	7	IRI data	Aerial photograph interpretation
Canopy cv.	Percent	60	52	16	IRI data	Aerial photograph interpretation
Elevation	Meters	1608	2826	258	Digital elevation model	Computed in GIS
Potential solar radiation	MJ cm^{-2} yr^{-1}	.80	.86	.15	Aspect, slope, and latitude	See McCune and Keon (2002)
Distance from streams	Meters	924	243	183	Boulder County GIS stream data	Computed in GIS

Table 2
Weather, wind and fuel moisture information for simulated fires.

	Walker Ranch Fire	Overland Fire
1-h fuel moisture (%)	4	4
10-h fuel moisture (%)	5	5
100-h fuel moisture (%)	6–7	6
Live herb. moisture (%)	31–40	35–40
Live woody moisture (%)	31–90	40–70
Temperature minimum (°F)	66	50
Temperature maximum (°F)	92	95
Relative humidity minimum (%)	8	9
Relative humidity maximum (%)	15	30
20-ft windspeed range (mph)	3–9	10–50
Wind direction range (D)	60–270	250–270
Wind gusts modeled?	No	Yes (50 mph)
Crown fire enabled?	Yes	Yes
Spot-fire ignition frequency (%)	0.5	0.07
Burn period (day/month, time)	9/15, 0530–9/17, 1730	10/29, 0530–10/29, 2000

slope-driven fire that burned 427 ha seven miles southwest of the city of Boulder on September 15–17, 2000. Both fires experienced suppression activities by fire fighting units and occurred late in the fire season when fuel moistures were extremely low.

3.6. Comparison to fuel maps from LANDFIRE

LANDFIRE national fuel maps (public communication, Landscape Fire and Resource Management Planning Tools Project, www.landfire.cr.usgs.gov, accessed 21 March, 2007) were used for wildfire simulation and comparison to the current study's maps. The same two historic fire events were used to evaluate the accuracy of fire spread rates and crown-fire activity simulated in FARSITE (Finney, 1998) using identical fire and weather inputs for LANDFIRE fuel maps and the current study's fuel maps.

4. Results

4.1. Fuel maps

The CART models accounted for 56–62% of the variance of predicted forest fuels (surface fuel model, canopy bulk density, canopy base height and canopy height). Optimally sized trees ranged from 12 leaves (11 splits) to 15 leaves. Above 15 leaves, no tree showed significant reduction in variance (Fig. A4). The average contribution of each predictor variable was calculated for all 4

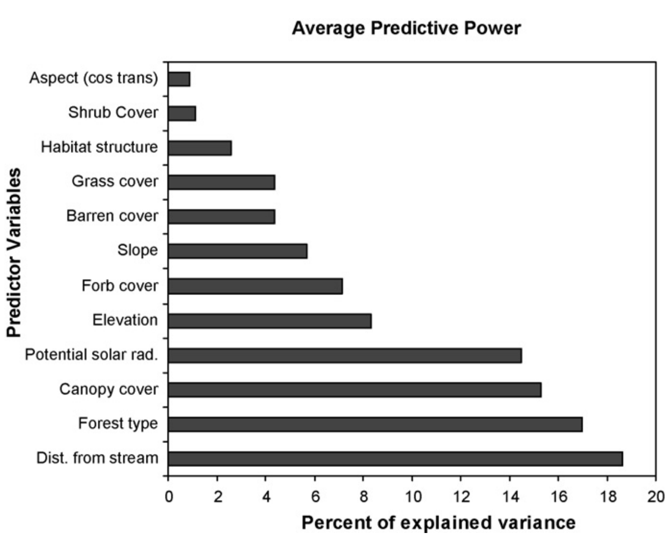

Fig. 2. Average power of each predictor variable for all predicted fuel parameters combined across all CART models.

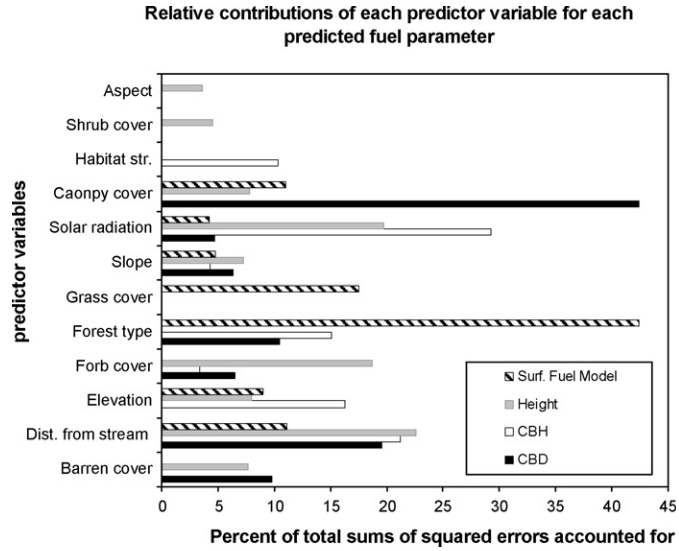

Fig. 3. Contribution of predictor variables in explaining variance from predictive models for canopy height, canopy base height, canopy bulk density, and surface fuel model.

predicted fuel parameters combined (Fig. 2) as well as for each fuel parameter individually (Fig. 3). Overall, distance to streams was the most powerful predictor variable, accounting for an average of 18.6% of the explained variance in all four CART models. Forest type was the second most powerful predictor, describing an average of 17% of the explained variance. Canopy cover and potential solar radiation were next accounting for 15.3% and 14.5% of the average explained variance, respectively. These four variables together accounted for over 60% of the explained variance in the fuel complex. The other nine predictor variables each accounted for less than 10% of the explained variance and comprise less than 40% of the total explanatory power of the classification and regression trees (Fig. 2).

4.1.1. Surface fuel model

The surface fuel model predictive tree had an R^2 of 0.564 and a cross-validated R^2 of 0.488 ($F = 14.00$, $p < 0.001$) (Fig. A1a). Forest type was the best predictor variable and accounted for 42.4% of the explained variance (Fig. 3). The second most important predictor variable was the percent of grass cover, which was estimated from aerial photographs and field surveys in the IRI dataset, and accounted for 17.5% of the explained variance. Distance from streams and canopy cover accounted for 11.1% and 11.0% of the explained variance, respectively. Seven fuel models were used to describe the forest fuels in the montane zone of Boulder County (Fig. A5). Timber Litter 8 (Long Needle Pine) was the most commonly used fuel model (32.5% of the montane zone) and was used extensively in ponderosa pine forests that lacked considerable understory vegetation. The second most common surface fuel model was Timber Litter 3 (Moderate Load Conifer Litter) which made up 18.6% of the montane zone. Anderson's #2 (Timber Grass/Understory) made up 16.7% of the montane zone and was assigned frequently to ponderosa pine forests that exhibited considerable understory vegetation.

4.1.2. Canopy bulk density

The optimal regression tree had 12 leaves, an R^2 of 0.623, and a cross-validated R^2 of 0.504 ($F = 13.01$, $p < 0.001$) (Fig. A1b). The average canopy bulk density for all plots was 0.1367 kg/m^3. The maximum value observed was 0.28 kg/m^3, and the minimum observed value was 0.0 kg/m^3. The strongest predictor was percent canopy cover, which alone accounted for 35% of the explained

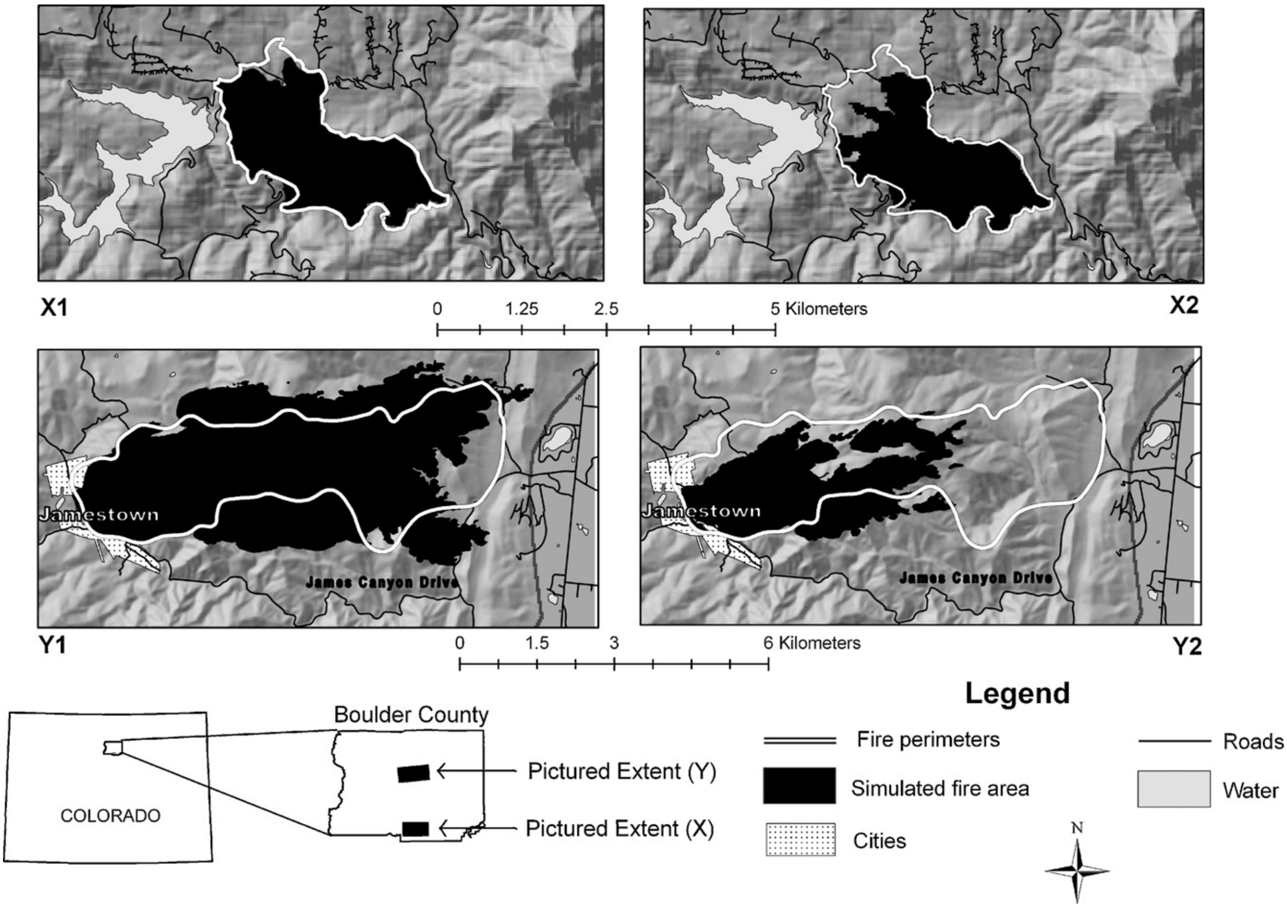

Fig. 4. Actual fire perimeter vs. predicted fire area for the Walker Ranch Fire (X) and the Overland Fire (Y) simulations. Current study fuel maps (X1 and Y1) vs. LANDFIRE fuel maps (X2 and Y2).

variance (Fig. 3). The second most important predictor was distance to streams, which accounted for 19.6% of the explained variance. Forest type and barren cover were the next best predictors accounting for 10.5% and 8.9% of the explained variance respectively.

4.1.3. Canopy base height

The optimal CART tree for canopy base height had 12 leaves, an R^2 of 0.582, and a cross-validated R^2 of 0.467 ($F = 14.20$, $p < 0.001$) (Fig. A1c). The average canopy base height for all plots was 1.1 m. The maximum value observed was 4.27 m, and the minimum observed value was 0.0 m. The most important predictors were potential solar radiation and distance from streams, which accounted for 29.3% and 21.2% of the variance, respectively (Fig. 3). Elevation and forest type were moderately important predictors which accounted for 16.3% and 15.1% of the explained variance, respectively.

4.1.4. Canopy height

The resultant predictive tree for canopy height explained 56.3% of the variance and contained 13 leaves ($R^2 = 0.563$, cross-validated $R^2 = 0.475$, $F = 10.12$, $p < 0.001$) (Fig. A1d). The average canopy height for all plots was 13.31 m. The highest value observed was 17.5 m, and the lowest observed value was 0.0 m. Distance from steams was the most highly correlated predictor variable, and accounted for 22.6% of the explained variance (Fig. 3). Potential solar radiation and forb cover were the second and third most powerful predictors for canopy height, accounting for 19.7 and 18.7% of the explained variance respectively. Together, distance from steams, potential solar radiation, and forb cover explained 61% of the variance in this predictive model. Elevation, canopy cover, barren cover, and slope were all moderately valuable predictor variables, each describing 7–8% of the variance.

4.2. Fuel map validation

4.2.1. Current study

The resultant fuel maps accurately simulated the spread rate and crown-fire activity of two previous fires in the study area. For the Walker Ranch fire, simulations using the current study's fuel maps burned 91.4% of the actual fire area during the actual burning

Table 3
Comparison of simulated and observed extent of the Walker Ranch and Overland Fires for the current study and LANDFIRE fuels data.

		Total simulated burn area (ha)	Percent of actual fire area burned in simulation	Simulated burn area (ha) outside actual fire perimeter (% of total simulated hectares)
Walker Ranch Fire	Current study simulation	398.43	91.4	8.37 (2.1)
	LANDFIRE simulation	340.47	77.7	8.85 (2.6)
Overland Fire	Current study simulation	2090.97	88.2	709.56 (34)
	LANDFIRE simulation	775.98	40.3	145.35 (19)

Table 4
Comparison of canopy fuel characteristics and average rate of spread (ROS) based on Overland Fire simulations for maps in the current study and those from LANDFIRE.

		Canopy cover (%)	Crown base height (m)	Canopy bulk density (kg/m^3)	ROS (m/min)
Minimum	Current study	0.00	0.00	0.0000	.01
	LANDFIRE	0.00	0.00	0.0000	.03
Maximum	Current study	80.00	4.27	0.2800	86.06
	LANDFIRE	95.00	10.0	0.1900	59.30
Mean	Current study	42.00	1.10	0.1367	5.75
	LANDFIRE	49.17	1.79	0.0637	3.58
Standard deviation	Current study	21.35	1.33	0.0465	9.92
	LANDFIRE	28.83	1.39	0.0366	6.16

period (Fig. 4, Table 3). Because this fire was limited by the barrier of South Boulder Creek on the east and south and was actively suppressed on the western and northern edges, the simulated fire reached the fire perimeter, but was not permitted to travel further (except for lofted embers that traveled over the perimeter barriers). Thus the proportion of the area within the actual fire perimeter that was burned in the fire simulation is illustrative of an accurate fire spread rate.

The Overland Fire, on the other hand, was an extreme one-day, wind-driven wildfire that was not actively suppressed for much of its eastward run (personal communication, Moraga R. & White C., 20 February, 2007). Successful suppression efforts were limited to a small hand-line on the south-western edge of the fire perimeter protecting the town of Jamestown and a back-burn at the eastern edge of the fire perimeter, close to Heil Ranch Road. For most of the simulation, the fire was allowed to 'spill over' into unburned areas. In this case, it is informative to examine both the percent of the actual fire area that was burned in each simulation as well as the percent of the simulated fire that burned outside the actual fire perimeter (Fig. 4, Table 3). The simulation using current study's

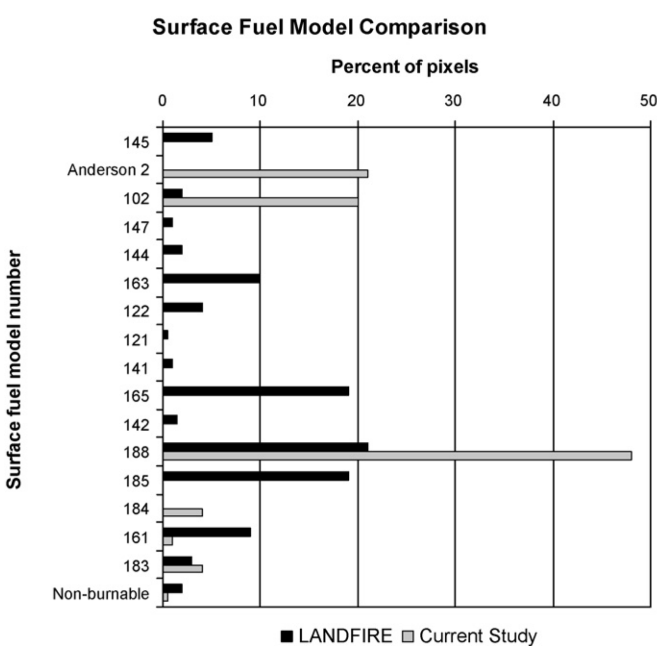

Fig. 5. Current study surface fuel models compared to LANDFIRE's surface fuel models (calculated for the area in and directly surrounding the Overland Fire perimeter). Fuel models are listed according to their spread rate. Model 145 had the highest spread rate and the non-burnable model had the slowest spread rate (spread rates compared for 10 mph winds, fuel moistures of 3, 4, 5, 30, and 60% for 10, 100, and 1000 h, herbaceous, and woody fuels respectively). All fuel model numbers refer to Scott and Burgan (2005) except Anderson's #2 (1982). See Supplemental Material for description and spread rates of each surface fuel model (Table A7).

fuel maps burned 1381 ha of the 1566 ha actual fire area (88.2% of the area within the actual perimeter), and another 710 ha beyond the actual fire perimeter (34% of the total simulated burn was outside the actual fire perimeter). Indeed, the rate of spread for the eastward movement of the flaming front was quite close to reality, but the north and south flanking behavior of the simulated fire traveled further than the actual fire event (Fig. 4).

4.2.2. LANDFIRE

In addition to evaluating fire simulations using the current study fuel maps, the national fuel maps from the LANDFIRE project for the study area were evaluated on the same fires with the same burning conditions. For the Walker Ranch fire, simulations using the LANDFIRE maps burned 77.7% of the area within the fire perimeter and had only a small spot-fire that initiated outside the perimeter. The spread rate was lower than the rate simulated from the current study's maps and thus a smaller percentage of the Walker Ranch fire area burned in this simulation (Fig. 4, Table 3).

The slower fire spread rate simulated for the LANDFIRE fuel parameters was more evident in the Overland Fire where the average rate of spread was 3.58 m/s compared to 5.75 m/s for the current study (Table 4). The LANDFIRE simulation burned 631 ha of the 1566 ha total fire area (40.3% of the area within the actual perimeter), and another 145 ha beyond the actual fire perimeter (19% of the total simulated burn was outside the actual fire perimeter) (Fig. 4, Table 3). In the area within and directly around the Overland Fire, the LANDFIRE surface fuel model map contained 15 different assignments (from Scott and Burgan's 40 fuel models, 2005), compared to 7 used in the current study (Fig. 5).

In the wind-driven Overland fire simulation, the LANDFIRE maps showed crown-fire activity (passive or active) on 36% of the burned pixels, whereas the current study showed crown fire in 55% of the burned pixels (Fig. A6). The Walker Ranch Fire was a slope- and fuel-driven fire and experienced only a fraction of the crown-fire activity that was observed in the Overland Fire. For the Walker Ranch fire, there were minor differences in crown-fire activity between the current study's fuel maps (13.8% of the pixels) and LANDFIRE fuel maps (15.8% of the pixels).

Overall, the LANDFIRE canopy fuel data shows some consistent trends when compared to the current study's fuel maps. For instance, compared to the current study's average values for the area in and surrounding the Overland Fire, LANDFIRE's average canopy base height is 0.69 m higher, canopy bulk density (0.0637 kg/m^3) is less than half (0.1367 kg/m^3), and average canopy cover is 7 percentage points higher (Table 4).

5. Discussion and conclusions

5.1. Predictive fuel mapping

The CART models accounted for 56% to 62% of the explained variance in forest fuels. The variable with the highest predictive power for all fuel parameters combined was distance from streams, which accounted for an average of 18.6% of the explained variance among the four fuel parameters (Fig. 2). In the relatively dry Front Range, distance from streams has an important influence on vegetation type, understory vegetation characteristics (Peet, 1981), and fuel characteristics which determine fire behavior. Another important predictor was potential solar radiation (largely determined by aspect), which accounted for an average of 14.5% of the explained variance. Surprisingly, neither of these variables is included in the conventional vegetation to fuels crosswalk that has commonly been used for fuel mapping (Reinhardt and Crookston, 2003; Stratton, 2006; personal communication, Seli R., 13 February, 2007). Fuel mapping would be greatly improved by incorporation of these simple physical variables that are easily derived in a GIS from a digital elevation model, which is commonly available.

The top five most important predictor variables: distance from streams, forest type, percent canopy cover, potential solar radiation, and elevation together accounted for an average of 73.7% of the explained variance in the four predicted fuel parameters. These variables are currently available in many forested areas and are not difficult to derive from remotely sensed data if not already available. With the addition of properly stratified field plots, the methods of this study have the potential to accurately map the surface and canopy fuels of large forested, fire-prone landscapes. In future research, the incorporation of LIDAR (Light Detection and Ranging) data, could provide even more robust predictions of canopy and surface fuel characteristics.

5.2. Limiting factors for understory fuels

The surface fuel model is a particularly important fuel parameter as it dictates the spread rate and flame length of the surface fire and is instrumental in determining the transition from a surface fire to a crown fire (Hall and Burke, 2006). A vitally important decision when predicting surface fuel models is whether or not understory vegetation will play a significant role in surface fire behavior, as fuel models that include these fine fuels have faster spread rates and longer flame lengths (Scott and Burgan, 2005). Typically, it is assumed that light is the only limiting resource for understory development, and canopy cover percentage (often interpreted with free or inexpensive remote sensed data) is utilized to predict the presence of a well developed understory. Using this logic, areas with a more open canopy will develop appreciable understory vegetation, whereas closed canopy areas will contain very limited understory cover. However, the observed pattern of understory vegetation in the present study reveals a more complex interaction of solar irradiance and soil moisture availability in the northern Front Range of Colorado. Of course plants need both light and moisture, but which one is most limiting to plant growth is determined by a complex interaction of a variety of environmental factors and plant characteristics.

In the present study, 44% of the plots predicted to have a surface fuel model that includes a significant understory component (Anderson #2, Grass 2, and Timber Understory 2) were predicted on the basis of moisture availability rather than light availability (Fig. A1a). Overall, distance from streams (an influence on soil moisture) was just as strong a predictor variable for surface fuel model as was percent canopy cover (Fig. 3). In some cases where water is more limiting than sunlight, such as low-elevation sites that are far from streams, the presence of appreciable understory plants is best predicted by factors that facilitate increased soil moisture, such as low potential solar radiation and level terrain. In these cases, percent canopy cover is no longer a useful predictor of understory growth, and increased solar radiation may actually hinder the development of understory plants. Surface fuel mapping techniques that utilize soil moisture characteristics as well as solar radiation will likely yield maps that more accurately represent the heterogeneity of the forest understory.

5.3. Evaluation of the LANDFIRE fuel maps

The LANDFIRE data layers have not undergone evaluation in many areas, and the current study may be the first to validate simulated fire behavior with these national fuel maps in the Colorado Front Range with historic fires. Through the simulation of two recent wildfires using FARSITE, the fire spread rate predicted on the basis of the LANDFIRE fuel maps were less accurate than the predictions based on the fuel maps developed in this study. This is likely due to surface fuel model assignments with low rates of spread and fireline intensity, as well as canopy fuel characteristics that reduced the incidence of crown fire.

Proper surface fuel model assignments are critical for modeling accurate fire behavior (Hall and Burke, 2006; Stratton, 2006). Some of the LANDFIRE surface fuel models have spread rates and flame lengths that are likely too low for the dry ponderosa pine-dominated montane zone of the eastern Rockies (Table A7). Specifically, fuel models 185 (Timber Litter 5—high load conifer litter) and 161 (Timber Understory 1—low load timber–grass–shrub) have spread rates and/or flame lengths that are too slow or low to accurately portray fire behavior in this area. More appropriate surface fuel models for this area would likely be 188 (Timber Litter 8—long needle litter) and 165 (Timber Understory 5–very high load timber–shrub). The current study found that the Anderson surface fuel model #2 (Timber Grass and Understory, 1982), which has a higher average spread rate and flame length than any of the Scott and Burgan Timber Understory models, worked well to simulate accurate spread rates for the conifer forests of the montane zone in Boulder County.

For the Overland Fire, where dry Chinook winds played a critical role in driving the fire, the LANDFIRE fuel maps under-predicted crown-fire activity and rate of spread when compared to the current study's fuel maps which exhibited relatively similar behavior to the actual fire (Fig. 4; personal communication, Moraga R. & White C., 20 February, 2007). There are likely four causes for the lower rates of crown fire produced by the LANDFIRE fuel maps versus fuel maps from the current study. Generally, LANDFIRE fuel maps had: (1) surface fuel models with lower fireline intensity, (2) higher canopy base height values, (3) lower canopy bulk density values, and (4) higher canopy cover values (Table 4). All of these factors contributed to a lower incidence of crown-fire for the simulations based on LANDFIRE maps (Fig. A6) (Van Wagner, 1977) (in a simulated wildfire, a more closed canopy blocks airflow to the understory, reducing the wind speed which in turn reduces the fireline intensity, thus reducing the likelihood of a crown-fire).

An important note is that the current study's fuel maps did undergo iterative calibration in order to match historic fire behavior. The goal was to create an accurate metric to which LANDFIRE maps could be compared. As a result, it is not surprising that the current study maps outperformed the LANDFIRE fuel maps, but this comparison is critically important to evaluate the accuracy and utility of the national LANDFIRE fuel products in FARSITE simulations.

One drawback to LANDFIRE fuel maps is the broad scale at which they were derived and the lack of abundant field plots to ground-truth the predictions. This mapping project is still quite new and offers great promise for easily accessible nationally consistent fuel maps. This effort will likely be improved with the incorporation of more local area information, especially more abundant fuel plot measurements that can capture fine-scale variability in fuels. The LANDFIRE developers currently have announcements on their website that indicate adjustments which should be made before using the maps for fire simulation. These announcements are consistent with the findings of this study, as they suggest that the canopy base heights be reduced, the canopy bulk densities be increased, and the canopy cover be reduced (LANDFIRE data notifications, http://www.landfire.gov/notifications.php, accessed 15 May, 2007).

5.4. Limitations of this study

Like many aspects of ecosystems, fuel parameters are dynamic, changing season to season and through the years. Fuel maps were created to depict current stand conditions and were validated with fires that occurred recently during the fire season (June–September). Their applicability outside of these conditions is uncertain. In addition, accurate fuel maps should incorporate information from disturbances that alter the fuel complex, such as fires, blow-downs, insect outbreaks, and past forest management activities. While information about some recent fires in the area was available, detailed information on past fuel treatments and insect outbreaks was not easily accessible and was not incorporated into the fuel maps.

FARSITE makes many assumptions that could affect its predictions of fire behavior and effects. Values such as canopy closure, canopy base height, and canopy bulk density are assumed to be uniform within areas designated with the same values, whereas in reality, more variability exists. The Rothermel (1972) surface fire spread equation, which is utilized by FARSITE, assumes that surface fuel is continuous, when in reality this is not always the case. FARSITE also assumes a constant wind speed and direction for the entire landscape. Windwizard software, which calculates the effect of topography on wind direction and speed was not available for this project (Butler et al., 2006). With gridded wind parameters created by Windwizard, it is likely that the fire simulations in this study would have been more accurate. Despite these limitations, if given accurate data, FARSITE is capable of approximating real fire behavior with high accuracy.

5.5. Management implications

The current study shows that potential solar radiation and distance from streams, both easily derived in a GIS, can greatly improve predictive fire modeling based on fuel maps derived from pre-existing cover type maps. Canopy cover was also a useful predictor variable that is often determined from aerial photos or satellite imagery and should be incorporated if it is available. Incorporation of these variables to predict fuel parameters will likely yield maps that more accurately reflect the inherent variability of forested environments than the typical vegetation-to-fuel crosswalk. As a consequence, more accurate fuels maps will yield fire simulations that more closely reflect actual wildfire behavior.

Today's wildland firefighting tactics include sophisticated tools that were not available 10 years ago. Using tools such as FARSITE (Finney, 1998), and FS Pro, firefighting units now have the capabilities to accurately predict the potential spread of wildfires (McDaniel, 2007). But accurate fuels information, which is essential for these predictions, is often the most difficult component to obtain. The methods and findings of this study have the potential to inform these agencies how to more effectively use existing LANDFIRE data or to create their own local area fuels maps. For example, validation with previous fire events, as illustrated in the current study, should precede any fire modeling activity so that the user may understand how well LANDFIRE data support simulation of real events.

Simulating active wildfires is only part of the utility of accurate fuels information. Land management agencies as well as communities in the Wildland–Urban Interface are increasingly turning to strategic fire mitigation practices that require accurate fuels information. Spatially explicit information about areas of high fire hazard and likely major paths of fire spread can be utilized in conjunction with values at risk to inform the placement of fuels reduction treatments. Accurate fuels data can be as important before a wildfire as it is during one.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.foreco.2009.01.020.

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