EVALUATING ASTER SATELLITE IMAGERY AND GRADIENT MODELING FOR MAPPING AND CHARACTEIZING WILDLAND FIRE FUELS

Michael J. Falkowski, MS Student
Paul Gessler, Associate Professor
Penelope Morgan, Professor
Alistair M.S. Smith, Postdoctoral Researcher
Department of Forest Resources
University of Idaho
Moscow, ID 83843-1133
Falk4587@uidaho.edu
Paulg@uidaho.edu
Pmorgan@uidaho.edu

Andrew T. Hudak, Research Forester
USFS Rocky Mountain Research Station
Moscow, ID 83843
Ahudak@fs.fed.us

ABSTRACT

Land managers need cost-effective methods for mapping and characterizing fire fuels quickly and accurately. The advent of sensors with increased spatial resolution may improve the accuracy and reduce the cost of fuels mapping. The objective of this research is to evaluate the accuracy and utility of imagery from the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) satellite and gradient modeling for mapping fuel layers for fire behavior modeling within FARSITE. An empirical model, based upon field data and spectral information from an ASTER image, was employed to test the efficacy of ASTER for mapping and characterizing canopy closure and crown bulk density. Surface fuel models (NFFL 1-13) were mapped using a classification tree based upon three gradient layers; potential vegetation type, cover type, and structural stage.

INTRODUCTION AND BACKGROUND

Wildland fire is an important issue facing local and regional land managers in the United States. Fires occurring in many parts of the western United States today are far more severe than fires that occurred before the suppression era (Arno and Brown, 1989; Hessburg *et al.* 2000). Increased fire size and severity coupled with an increase in the number of people living in the wildland-urban interface has resulted in millions of dollars of damage to property and loss of life throughout the western United States in recent years. In 2002, federal agencies spent an estimated $1.6 billion on fire suppression (National Interagency Fire Center, 2003). As human populations move closer to the edges of wildlands, their lives and property become increasingly threatened by wildfire. In order to reduce fire risk to people and their homes, land managers must prioritize areas for fire mitigation and hazardous fuels reduction. In 2000, the US Department of Agriculture teamed with the Department of Interior and the National Association of State Foresters to develop the National Fire Plan (www.fireplan.gov). Along with post-fire rehabilitation and maintaining firefighting preparedness, the goals of the National Fire Plan include reducing fuels in at-risk areas, particularly in and around the wildland urban interface (Bisson *et al.*, 2003). Each year, the National Fire Plan provides funds to local fire districts to increase fire suppression capabilities and implement fuels reduction projects (USDA, 2000). In order to utilize monies from the National Fire Plan efficiently, land managers need cost-effective methods for mapping and characterizing fire fuels quickly and accurately. Some of the most potentially useful approaches for accomplishing this involve the integration of remote sensing (RS), Geographic Information System's (GIS), field data and gradient modeling. Such analyses could provide consistent maps of fire fuel conditions across a diversity of land ownerships.

Fuel Mapping

One of the most important factors influencing fire hazard and fire risk is the type, composition, and distribution of fuels (Chuvieco and Congalton, 1989). Wildland fuels are typically divided into three strata: ground fuels, surface fuels, and crown fuels (Pyne *et al.*, 1996). Ground fuels consist of roots, duff, and buried woody debris. Fires burning in this stratum usually exhibit slow rates of spread. Surface fuels are composed of leaf litter, coarse woody debris, seedlings, saplings, and herbaceous vegetation. Most wildland fires start in, and are carried by, the surface fuel strata. Overstory trees and shrubs comprise the crown fuel strata. Fires burning in the crown fuel strata are often extremely intense and nearly impossible to control (Pyne *et al.*, 1996). Since fuel stratum relationships are extremely complex, fire managers often describe fuels by grouping vegetation communities, based upon similar potential fire behavior, into fuel types (Riano *et al.*, 2002) or fuel models (Anderson, 1982). However, since the distribution and accumulation of fuels is highly variable (Brown, 1979) and, in forested areas, highly dependent upon vegetation type as well as stand history (Keane *et al.*, 2001; Brandis and Jacobson, 2003) fuel quantity and distribution are not directly related to fuel types (Pyne *et al.*, 1996).

Field Mapping of Fuels. Prior to the development of remote sensing technologies, fuels were typically mapped through extensive field inventory (Miller *et al.*, 2003). Although these technologies were successful, the development of remote sensing technologies could potentially reduce the cost and time required to map fuels on the ground (Keane *et al.*, 2001). Remote sensing technology also has the potential to update fuel maps quickly in areas where conditions are dynamic due to logging, fire, or other changes.

Remote Sensing of Crown Fuels. Traditionally, interpretation of aerial photography coupled with field data was the primary method used to map fire-related canopy variables (Riano *et al.*, 2003) such as crown bulk density, crown closure, and canopy height. More recently empirical methods, which are less labor intensive, have been used to estimate these variables from Landsat TM and SPOT (Systeme Probatoire D'Observation de la Terre) HRV (high resolution visible) data (Riano *et al.*, 2003). Franklin *et al.* (2003) mapped various stand attribute classes, including canopy height and crown closure, through the classification of spectral and textural information derived from Landsat 5 data. Miller *et al.* (2003) successfully mapped structural stage classes in Arizona by running Landsat TM data through a clustering algorithm.

Remote Sensing of Surface Fuels. The inability of optical sensors, such as Landsat TM and MSS, to penetrate the forest canopy (Miller *et al.*, 2003) limits their utility for mapping surface fuels (Keane *et al.*, 2002). As a result, most studies using remote sensing to characterize surface fuels first classify an image into vegetation categories and assign fuel types or fuel models to each category (Keane *et al.*, 2001). Chuvieco and Salas (1996) characterized fuel types through the classification of Landsat Thematic Mapper (Landsat TM) data. Chuviceo and Congalton (1989) and Castro and Chuvieco (1998) used similar methods to map fuel types in Spain and Chile, respectively. Wilson *et al.* (1994) applied maximum likelihood decision rules to a Landsat Multi-Spectral Scanner (Landsat MSS) image to directly classify fuel types across Wood Buffalo National Park, Canada. Riano *et al.* (2002) improved a fuel type classification by incorporating two seasonal Landsat TM images, to account for phenological differences in vegetation, into a classification algorithm. Hyperspectral remote sensing has also been used to map fuel types and vegetation moisture content for a chaparral community in Southern California (Roberts *et al.*, 1998).

Gradient Modeling of Fuels. Gradient modeling refers to the use of environmental gradients (topographical, biogeochemical, biophysical, and vegetational) to model the occurrence of natural phenomena (Keane *et al.*, 2002). This approach has been used with moderate success in estimating fuel types and fuel loading. Environmental gradients such as topography, moisture, and time since last burn have a large impact on fuel loading (Kessell, 1979). High fuel loading, for example, can be partially explained by lower decomposition rates (characterized by moisture and temperature gradients) and a long time interval since the last fire (Keane *et al.*, 2001). Gradient modeling has been used to model fuel characteristics in Glacier National Park, Montana (Kessel, 1979).

Integrated Fuels Mapping. The integration of remote sensing and gradient modeling may also increase the accuracy of fuels mapping projects. For example, Keane *et al.* (2002) integrated remote sensing and gradient modeling to map fuels across the Gila National Forest in New Mexico. This approach, termed the ‘vegetation triplet’, incorporates three layers: potential vegetation type (PVT), cover type (CT), and structural stage (SS). PVT is a site classification based upon the climax vegetation that would be found on a site in the absence of disturbance (Keane *et al.*, 2002; Smith *et al.*, 2003). CT describes the dominant species found on a site, and SS refers to the current canopy structure of a site. PVT is directly related to the biophysical setting of a site, which ultimately determines the site’s productivity and decomposition rates, and therefore has a large impact on fuel characteristics (Keane *et al.*, 2002). CT is important for fuels mapping because dead woody debris and litter are directly related to the dominant tree species found on the site (Keane *et al.*, 2002). The potential of a surface fire spreading to the crown is highly dependent upon the vertical structure of the stand, which is described by SS. The triplet approach has been used to assess the hazard of forest disease outbreak, and vulnerability to fire in the Columbia basin

(Hessburg *et al.*, 2000); it has been used in the Gila National Forest and the Selway-Bitteroot Wilderness, to map fuels and input layers required to run FARSITE (Keane *et al.*, 2001; Keane *et al.*, 2002).

Future of Fuels Mapping. Remote sensing based fuels mapping has typically employed one of the Landsat sensors (MSS, TM, or ETM+) to map fuels characteristics (Riano *et al.*, 2003). Although these sensors are effective, and are widely applicable to many environmental mapping and monitoring situations, the advent of new sensors with improved spatial and spectral resolutions may improve the accuracy (Chuviceo and Congalton, 1989) and reduce the cost (Zhu and Blumberg, 2001) of forest fire fuel mapping. ASTER, a sensor aboard NASA's Terra platform (see specifications (Table 1), has untested potential for characterizing and mapping forest fire fuels. The visible and near-infrared telescope (VNIR), which collects data with a spatial resolution of 15 m in the green (0.52 – 0.60 µm), red (0.63-0.69 µm), and near infrared (0.76 - 0.86 µm) portions of the electromagnetic spectrum, should be particularly useful for obtaining information about vegetation (Rowan and Mars, 2003), and may prove successful in mapping fuel characteristics.

Table 1. ASTER specifications (adapted from Abrams, 2003)

Spectral Region	Spatial Resolution (m)	Channel	Bandwidth (µm)
VNIR telescope	15	1	0.52 - 0.60
	15	2	0.63 - 0.69
	15	3	0.76 - 0.86
SWIR telescope	30	4	1.60 - 1.70
	30	5	2.145 – 2.185
	30	6	2.185 – 2.225
	30	7	2.235 – 2.285
	30	8	2.295 – 2.369
	30	9	2.360 – 2.430
TIR telescope	90	10	8.125 – 8.475
	90	11	8.475 – 8.825
	90	12	8.925 – 9.275
	90	13	10.25 – 10.95
	90	14	10.94 – 11.65

The objective of this research is to evaluate the accuracy and utility of ASTER satellite imagery coupled with gradient modeling for mapping fuel layers for fire modeling with FARSITE. We will develop spatial predictions of surface fuel models (NFFL 1-13 (Anderson, 1982)) and crown fuel characteristics such as crown bulk density and canopy closure. Field data from a Moscow Mountain pilot study area will then be used to evaluate the results.

METHODS

Study Area

Moscow Mountain (Figure 1), the extreme western extension of the Clearwater Mountains, is located approximately 9 km northeast of the city of Moscow, Idaho (Latitude 46º 44'N, Longitude 116º 58' W). This area encompasses approximately 25,000 hectares of mixed conifer forest and is topographically diverse, with gentle to moderately steep slopes on many different aspects. There are also many homes, buildings, and private properties interspersed with large tracts of forestland. This areas diverse management history and land ownership has created a complex mosaic of forest structure and fuel, making it an excellent place to test the efficacy of satellite sensor imagery for characterizing forest fire fuels. Some parts of the forests have been logged multiple times; others have had little to no logging. Prescribed burning is used often as part of forest management practices on some, but not all lands to accomplish site preparation and other vegetation management goals. For instance, the University of Idaho Experimental Forest implement prescribed burns across 1-2% of their forest annually. The resulting mixed conifer forests are very diverse in species composition and in forest structure, and surface fuel loading varies greatly.

Sample Design

Eighty-three field plots were located using a two-stage (stratified systematic) sample design. For the first stage, nine strata were constructed based upon unique combinations of three elevation strata and three solar insolation strata. Solar insolation was calculated from a 30m USGS digital elevation model (DEM) for the growing season (mid-April – late September) using the Solar Analyst (HEMI, 2000) software package. Solar insolation and elevation were each partitioned into three individual strata. The resulting strata were then crossed to provide nine combinations of the three solar insolation and three elevation strata. Elevation and solar insolation were chosen because they are directly related to the biophysical gradients over the study area. They also characterize the biophysical potential of a site, and therefore have a large impact upon fuel dynamics (Keane *et al.*, 2002). For the second stage, Leaf area index (LAI) values, derived from an empirical model using NDVI calculated from a LANDSAT ETM+ image (Pocewicz *et al.*, *In press*), was assigned to each of the nine strata and ranked from low to high. Plots were then systematically selected across each stratum's LAI gradient.

Data Collection

The development of new technologies, and the need for up-to-date fuels information, has lead to the creation of new initiatives aimed at mapping and monitoring fuels and fire effects nationwide. In order to be effective, such initiatives need to collect data in a consistent manner. As a result, the USDA Forest Service developed a new sampling protocol, called FIREMON (http://fire.org/firemon/). This new protocol is structured in a way that makes it applicable to many fuels management scenarios.

Surface and crown fuels were inventoried at each plot with sampling procedures adapted from the FIREMON sampling protocol. A 405 m^2 fixed radius plot, which has a radius of 11.35 m (Figure 2), was used for tree measurements. The diameter at breast height (DBH), percent live crown, species, distance from plot center, bearing, and quadrant (NE, SE, SW or NW) was recorded for every tree or snag $\geq$ 2.7 cm DBH within the fixed-radius plot. A variable radius plot (15 m^2/ha) was used to identify large trees or snags outside the fixed radius plot. The same variables were recorded for each tree or snag captured with the prism. Height, height to live crown, and both the major and minor crown diameter, were measured for the trees with the largest and smallest DBH for each species within each quadrant. Canopy density was measured using a spherical densiometer at the northern, eastern, southern, and western corners of the fixed-radius plot (Figure 2).

Downed woody debris (DWD) was measured along four transects (Figure 2). One-hour fuels (DWD 0-0.635 cm diameter) and ten-hour fuels (DWD 0.635-2.54 cm diameter) were tallied along the first 1.8 m of each transect. One hundred-hour fuels (DWD 2.54-7.62 cm diameter) were tallied along the first 4.6 m of each transect. The diameter of one thousand-hour fuels (DWD > 7.62 cm diameter) was recorded along the entire length of each transect. Litter and duff depths were measured 4.6 m from the beginning of each 16.06 m transect. Visual estimates of percent canopy cover by vegetation class (sapling, seedling, shrub (tall, med. and low), grass, forb, fern, moss/lichen, and litter) were made within four 4 x 4 m subplots centered over the midpoint of each DWD transect (8 m from beginning). Potential vegetation type, slope, and aspect were also measured and recorded at each plot.

ASTER Image Processing

A Level 1B (VNIR registered radiance at the sensor) ASTER image, acquired on September 10, 2002, was purchased through the Earth Observing System (EOS) Data Gateway. The ASTER image was imported into the ERDAS Imagine image-processing software using the built-in ASTER import dialog. Once imported, a geometric registration was performed and radiance values were converted to reflectance. Vegetation indices, such as the normalized vegetation index (NDVI [NIR - R / NIR + R]), simple ratio (SR [NIR / R]), and green-red ratio vegetation index (GRVI [Green - Red / Green + Red]), were calculated from the processed ASTER image.

Surface Fuel Model Layer Development

Surface fuel models were mapped across the study area by implementing the aforementioned "vegetation triplet" (Keane *et al.*, 2002). A supervised classification (maximum likelihood) routine was used to map CT and SS from the ASTER imagery. The PVT and final surface fuel model layers were developed using a classification tree algorithm within the S-Plus statistical software package. The tree algorithm uses training sets to develop classification rules by recursively partitioning training data into categories, with each split chosen to maximize differences between the two resultant groups (Lawrence and Wright, 2001). Classification trees are ideal for modeling and mapping landscape attributes such as PVT and surface fuel model because the data can be both categorical and continuous and are not required to meet any assumptions such as normality and homoscedasticity. Classification trees are also able to deal with nonlinearity and are fairly easy to implement and interpret as compared to other multivariate techniques (McBratney *et al.*, 2003). A detailed discussion of the techniques used to produce each layer follows.

PVT Layer Development. PVTs were mapped across our study area through the implementation of classification tree decision rules based upon PVT (series level habitat types based upon Cooper *et al.*, 1991) and topographical variables (elevation, slope, and aspect) at each of our 83 field plots. Elevation, slope, and aspect were chosen to classify PVT because they are surrogates for biophysical setting, and therefore directly influence the vegetation community composition (Smith *et al.*, 2003). A 10-meter USGS DEM was resampled to the same resolution as the ASTER image (15m) using a nearest neighbor algorithm within ArcGIS. The resampling procedure was performed to ensure each input (CT, SS, PVT) and output (canopy closure, crown bulk density, and surface fuel model) had the same spatial resolution. PVT classification rules were derived from a classification tree using slope, aspect, and elevation as predictor variables. The final PVT classification rules were then applied across the entire study area to create the final PVT layer.

CT and SS Layer Development. CT, based upon the Society of American Foresters cover type classification scheme (Eyre, 1980), and SS, based upon the Interior Columbia Basin Management Project's (ICBMP) structural stage classification scheme (O'Hara *et al.*, 1996), were mapped across the Moscow Mountain study area through the implementation of a maximum likelihood supervised classification algorithm in ERDAS Imagine. Field data (our eighty-three field plots) and local expert knowledge were used to assign training data used in the classification.

Final Surface Fuel Model Layer Development. PVT, CT, and SS layers were input as predictor variables in a classification tree to derive surface fuel model classification rules based upon field data. These classification rules were then applied across the entire study area to create the final surface fuel model layer (Figure 3).

Canopy Fuel Layer Development

An empirical model (ordinary least squares regression), based upon field data and ASTER data, was employed to test the efficacy of ASTER for mapping and characterizing canopy closure and crown bulk density. Canopy closure and crown bulk density were calculated at the plot level based upon densiometer measurements and the Forest Vegetation Simulator (Stage, 1973), respectively. Initial data analysis was carried out in S-Plus to determine which variables to include in the final empirical models. Models were evaluated based upon the R^2, RMSE, and the Akaike Information Criterion (AIC) (Akaike, 1974). AIC evaluates model fit by penalizing the residual deviance by the number of parameters contained in the model (Gessler *et al.* 2000). Lower AIC statistics indicate better fitting models. Combinations of vegetation indices (NDVI, GRVI and SR) calculated from the ASTER image, were tested as predictor variables. In total, four regression models (Table 2) were compared for each response variable (canopy closure and crown bulk density). Model coefficients were extracted (Table 3) from the best model for each response variable and incorporated into an algorithm within ERDAS Imagine to create the final canopy closure and crown bulk density layers (Figures 4 and 5, respectively).

Table 2. Canopy Model Results

Model	Response	Predictor(s)	R^2	RMSE	AIC
1	Canopy Closure	NDVI	0.69	18.91%	727.50
2	Canopy Closure	GRVI	0.76	16.68%	706.67
3	Canopy Closure	SR	0.65	20.11%	737.70
4	Canopy Closure	NDVI + GRVI	0.77	16.56%	706.50
5	Bulk Density	NDVI	0.35	0.0092 Kg/m^3	-537.93
6	Bulk Density	GRVI	0.46	0.0084 Kg/m^3	-553.04
7	Bulk Density	SR NDVI +	0.36	0.0092 Kg/m^3	-538.69
8	Bulk Density	GRVI	0.47	0.0085 Kg/m^3	-551.84

(All regressions are significant at the 99.5% confidence level)

RESULTS AND DISCUSSION

The model containing both GRVI and NDVI (model 4) as predictors of canopy closure obtained the highest R^2, lowest RMSE, and lowest AIC values as compared to the other canopy closure models (Models 1-3), therefore it was selected as the optimum model for predicting canopy closure. Model 8 had a slightly higher R^2 than model 6. However, since Model 6 attained the lowest RMSE and AIC it was identified as the optimal model for predicting crown bulk density.

Table 3. Canopy Model Coefficients

Model	Coefficients	Value
4	Intercept	-22.97
	NDVI	66.61
	GRVI	297.00
6	Intercept	-0.0036
	GRVI	0.0991

Prior studies have used remote sensing to provide estimates of crown closure (canopy closure). For instance, Franklin *et al.* 2003 demonstrated that significant relationships exist between band five (MIR) of the Landsat sensor and canopy closure for two conifer species (jack pine: $R^2 = 0.30$, $p < 0.005$; white spruce: $R^2 = 0.32$, $p < 0.005$). However, when jack pine was considered alone a stronger relationship ($R^2 = 0.66$, $p < 0.005$) was achieved between the reflectance of band 4

(NIR) and canopy closure. The study by Franklin *et al.* 2003 was limited in that it only examined relationships between the reflectances of single Landsat bands and canopy closure. The current study demonstrates that the use of vegetation indices that incorporate visible and near infrared reflectances produce relationships similar in strength to those achieved by Franklin *et al.* (2003) ($R^2 > 0.65$, $p < 0.005$). However, use of GRVI solely or in combination with NDVI achieves stronger relationships ($R^2 > 0.76$, $p < 0.005$).

Only a few previous studies have implemented remote sensing to estimate crown bulk density, and in general these have not included a rigorous assessment of accuracy (Riano *et al.*, 2003). For example, Riano *et al.* (2003) investigated the potential of lidar to estimate forest parameters such as crown bulk density and foliage biomass, and highlighted the need for rigorous assessment of such relationships between remotely sensed data and fuel variables. However, Keane *et al.* (2002) estimated crown bulk density using the "vegetation triplet" methodology achieved only a poor relationship ($R^2 = 0.35$, $p < 0.005$). A comparison of this result with the GRVI and NDVI empirical model (model 8) demonstrates that a significant improvement ($R^2 = 0.47$, $p < 0.005$) is achieved by employing this vegetation index.

CONCLUSIONS

Overall, ASTER satellite imagery coupled with gradient modeling proved to be effective tools for mapping and characterizing wildland fire fuels across the Moscow Mountain study area. The "vegetation triplet" methodology presented herein identified surface fuel models that agree with local expert knowledge of existing forest fuel conditions. Each of the predictor layers derived for this study (i.e. PVT, CT and SS) also corresponds to local expert knowledge of existing conditions. However, before final conclusions about this analysis can be drawn, the quality of each layer requires thorough and quantitative accuracy assessment. Such an assessment will be conducted in the summer of 2004 across the study area.

Utilizing empirical relationships between ASTER satellite imagery and field data proved successful for mapping canopy fuels. The canopy fuel mapping analysis within the current study demonstrate that significant improvement is achieved through the use of vegetation indices over the use of single bands, which suggests that further analysis is required to assess the efficacy of other vegetation indices for estimating canopy fuel parameters.

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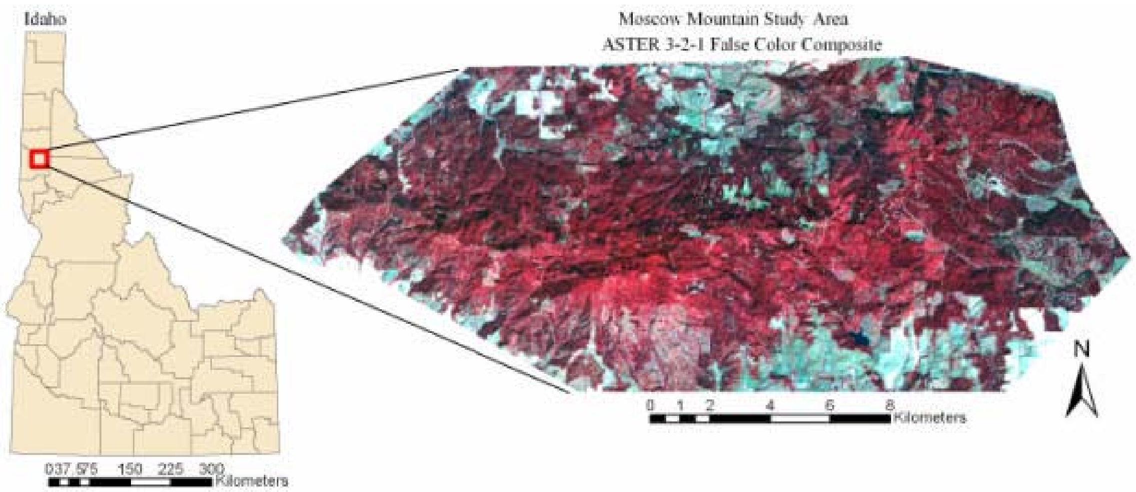

Figure 1. Moscow Mountain Study Area - An ASTER image displayed in a 3(NIR) -2(RED) - 1(GREEN) false color composite.

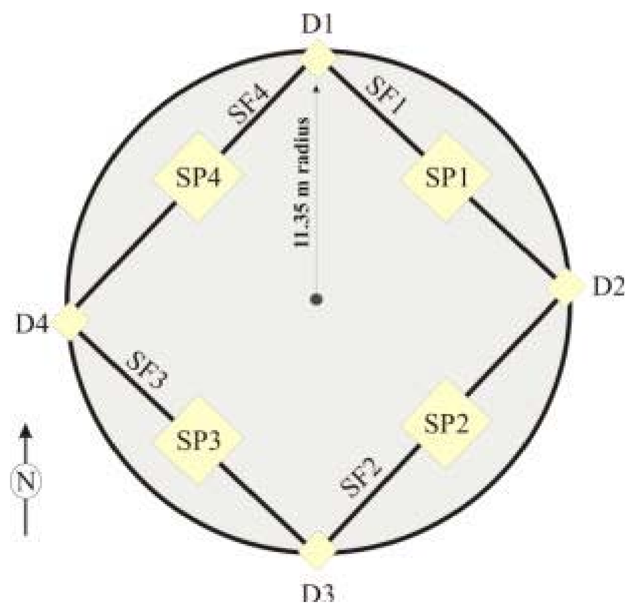

Figure 2. Plot Layout Diagram: SF1-4 = Surface Fuel Transects, D1-4 = Densiometer Reading Locations, SP1-3 = Vegetation Subplot Locations.

Figure 3. Final Fuels Layer – Fuel Models NFFL 1-13 (Anderson, 1982).

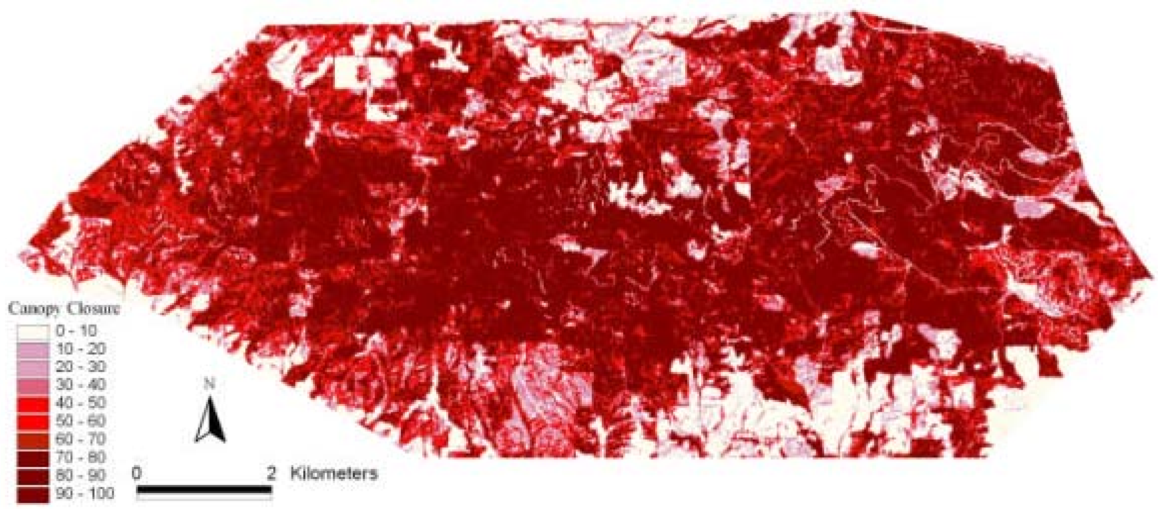

Figure 4. Final Canopy Closure Layer (% Canopy Closure).

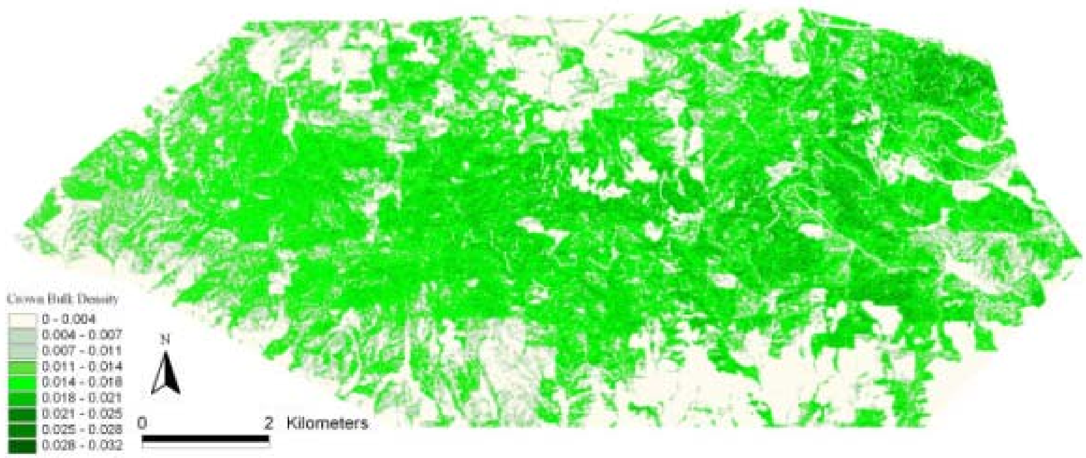

Figure 5. Final Crown Bulk Density Layer (Kg/m^3).

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