EVALUATING THE ASTER SENSOR FOR MAPPING AND CHARACTERIZING FOREST FIRE FUELS IN NORTHERN IDAHO

Michael J. Falkowski, MS Student [1]
Paul Gessler, Associate Professor [1]
Penelope Morgan, Professor [1]
Andrew T. Hudak, Research Forester [2]
Alistair M.S. Smith, Postdoctoral Researcher [1]
[1] Department of Forest Resources
University of Idaho
Moscow, ID 83843-1133
Falk4587@uidaho.edu
Paulg@uidaho.edu
Pmorgan@uidaho.edu
[2] 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 and FLAMMAP. Empirical models, based upon field data and spectral information from an ASTER image, were 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). Initiatives such as the national fire plan Recent federal initiatives provide funding to state and local governments that develop plans for identifying and mitigating hazards associated with wildland fire in the urban interface. 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

The type, composition, and distribution of fuels (Chuvieco and Congalton, 1989) is one of the most important factors influencing fire hazard and fire risk. 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: Fuels were typically mapped through extensive field inventory prior to the development of remote sensing technologies (Miller *et al.*, 2003). Although field inventories of fuels were successful, the development of remote sensing technologies reduced 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, fire-related canopy variables such as crown bulk density, crown closure, and canopy height were mapped based upon aerial photography interpretation and field data (Riano *et al.*, 2003). More recently empirical methods, which are less labor intensive, have been used to estimate these variables from satellite sensors such as Landsat TM and SPOT (Systeme Probatoire D'Observation de la Terre) HRV (high resolution visible) (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 Gla 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

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

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.

The objective of this research is to evaluate the accuracy and utility of ASTER satellite imagery coupled with gradient modeling for mapping fuel layers required for fire modeling within the FARSITE and FLAMMAP fire models, which are used to simulate fire growth (Finney, 1998) and predict potential fire behavior characteristics, (Joint Fire Science Program 2003) respectively. Specifically, spatial predictions of surface fuel models (NFFL 1-13 (Anderson, 1982)) and crown fuel characteristics such as crown bulk density and canopy closure will be developed.

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). A local landmark in the midst of an agricultural region, it is covered by about 25,000 hectares of mixed conifer forest. The mountain is topographically diverse, with gentle to moderately steep slopes on varying aspects. Moscow Mountain is under multiple ownership representing differing land management objectives. Existing land uses include private home sites, commercial building sites, commercial logging, research forestry, and recreation. Some of the forested lands have been logged multiple times; others have had little or no logging. Prescribed burning is used as a management tool in the university-managed forest and on the commercial timberlands. The resulting mixed conifer forests are variable in structure and species composition; surface fuel loading, the dry weight of combustible materials per acre, 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 m² 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 m²/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 eighty-three 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. The R^2, root mean square error (RMSE), and the Akaike Information Criterion (AIC) (Akaike, 1974) statistics were examined to evaluate the performance of each model. 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

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	0.36	0.0092 Kg/m^3	-538.69
8	Bulk Density	NDVI + GRVI	0.47	0.0085 Kg/m^3	-551.84

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

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).

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.

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

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

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 empirical model (model 6) demonstrates that a significant improvement ($R^2 = 0.46$, $p < 0.005$) 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 integration of remote sensing and gradient modeling 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 portion of the 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 is currently (summer of 2004) being conducted across the study area.

Employing 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.
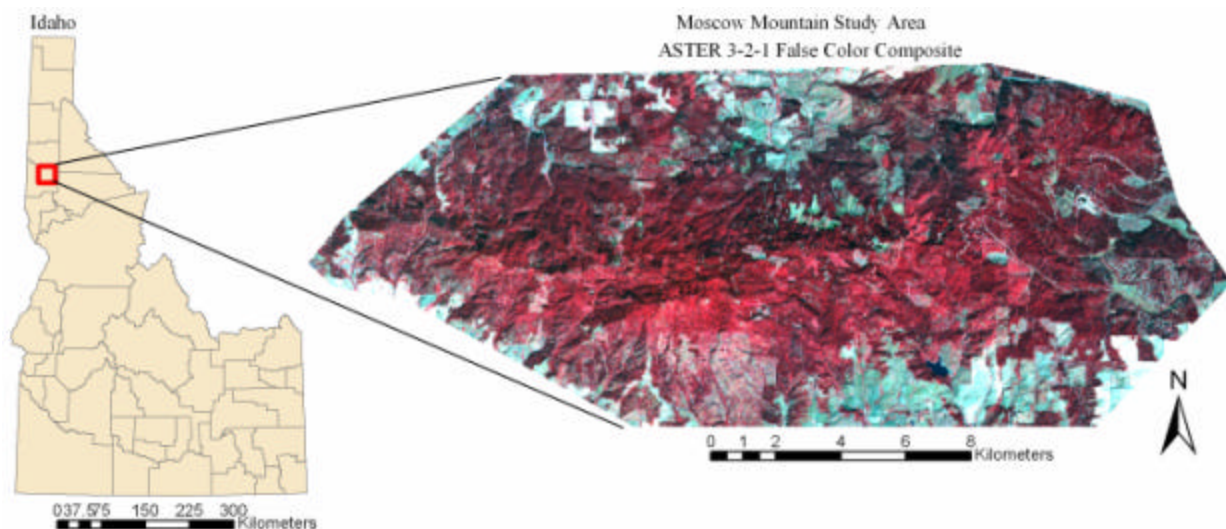
ACKNOWLEDGMENTS

Figure 1. Moscow Mountain Study Area - An ASTER image displayed in a 3(NIR) - 2(RED) - 1(GREEN) false color composite.
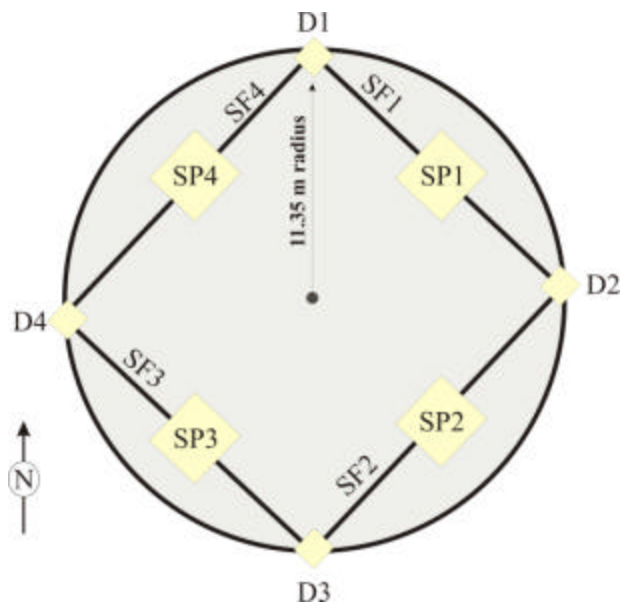
Figure 2. Plot Layout Diagram: SF1-4 = Surface Fuel Transects, D1-4 = Densiometer Reading Locations, SP1-3 = Vegetation Subplot Locations.
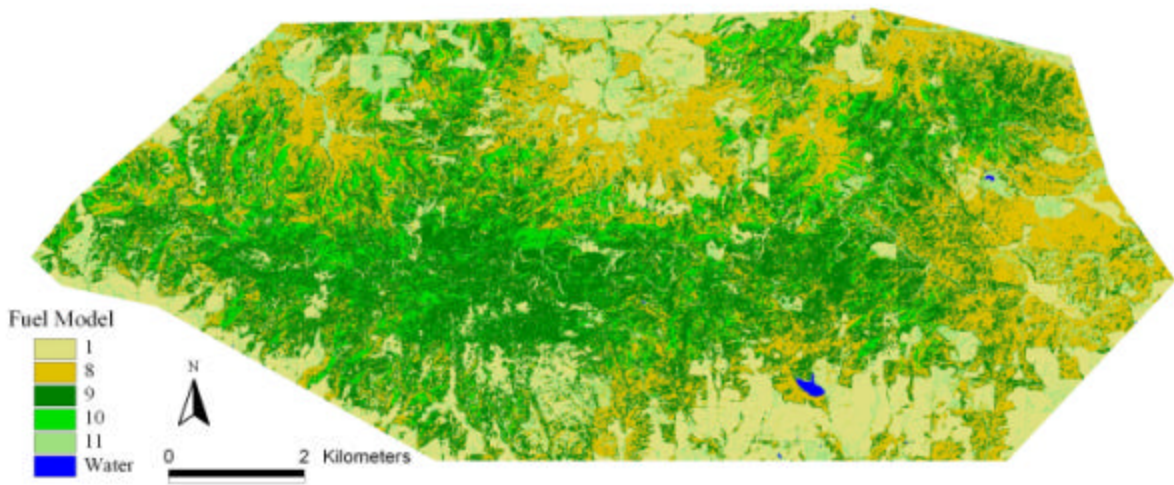

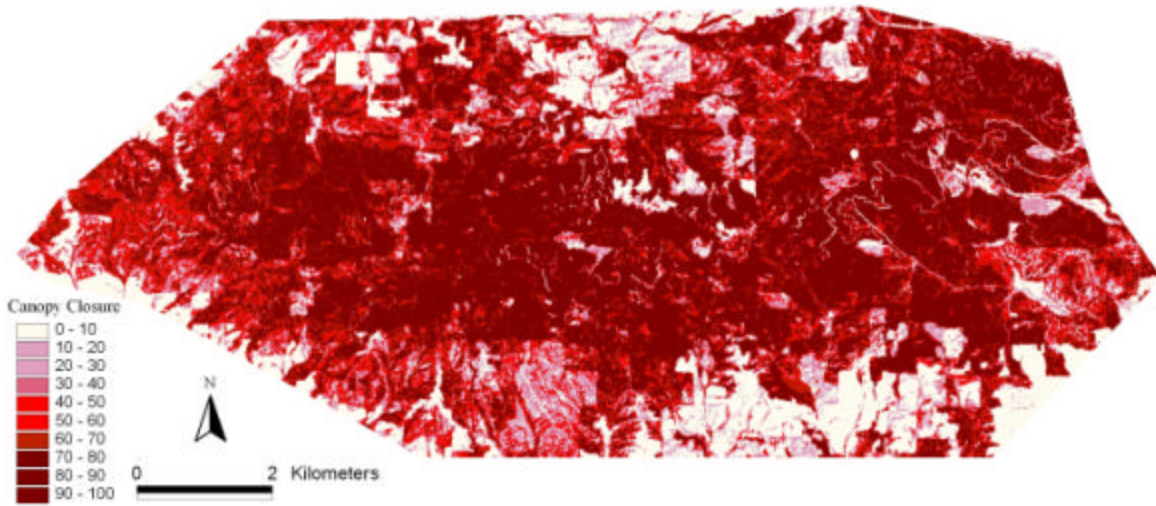**Figure 3.** Final Fuels Layer – Fuel Models NFFL 1-13 (Anderson, 1982).

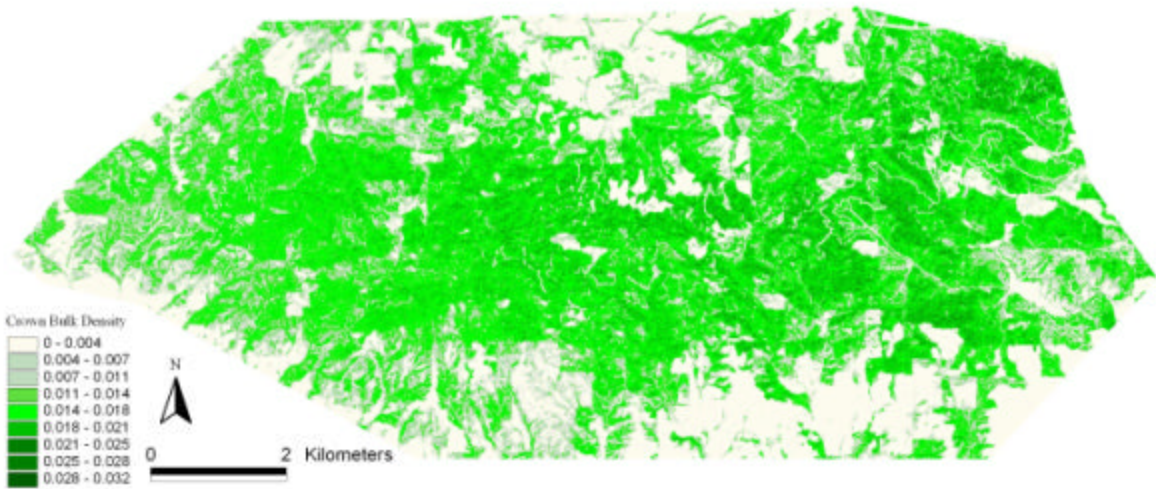**Figure 4.** Final Canopy Closure Layer (% Canopy Closure).

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

REFRENCES

Akaike, H. (1974). A new look at statistical model identification. IEEE Transactions on Automatic Control AU-19, pp. 716-722

Abrams, M. (2003). The Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER): data products for the high spatial resolution imager on NASA's Terra platform. *International Journal of Remote Sensing*, 21(5):847-859.

Anderson, H.E. (1980). Aids to determining fuel models for estimating fire behavior. General Technical Report. INT-122. Ogden, UT: U.S. Department of Agriculture - Forest Service, Intermountain Research Station, pp. 1- 22.

Arno, S.F., and J.K. Brown (1989). Managing fire in our forests-time for a new initiative. *Journal of Forestry*. 87:200-207.

Bisson, P.A., R.E. Rieman, C. Luce, P.F. Hessburg, D.C. Lee, J.L. Kershner, G.H. Reeves, R.E. and Gresswell, (2003). Fire and aquatic ecosystems of the western USA: current knowledge and key questions. *Forest Ecology and Management*. 178:213-229.

Brandis, K., and C. Jacobson (2003). Estimation of vegetative fuel loads using Landsat TM imagery in New South Wales, Australia. *International Journal of Wildland Fire*. 12:185-194.

Castro, R., and E. Chuvieco (1998). Modeling forest fire danger from geographic information systems. *Geocarto International* 13(1)15-23.

Chuvieco, E. and R.G. Congalton (1989). Application of remote sensing and geographic information systems to forest fire hazard mapping. *Remote Sensing of Environment*. 29:147-159.

Chuvieco, E. and J. Salas (1996). Mapping the spatial distribution of forest fire danger using GIS. *International Journal of Geographical Information Systems*. 10(3):333-345.

Cooper, S.V., K.E. Neiman, and D.W. Roberts (1991*). Forest Habitat Types on Northern Idaho: A Second Approximation*. General Technical Report. INT-236. Ogden, UT: U.S. Department of Agriculture - Forest Service, Intermountain Research Station, pp. 1- 143.

Eyre F.H. (1980). *Forest Cover Types of the Unisted States and Canada*. Society of American Foresters, Washington, D.C., pp. 1-148.

Finney, M. A. 1998. FARSITE: Fire area simulator - model development and evaluation. Research Paper RMRS-RP-4. Fort Collins, CO: USDA Forest Service, Rocky Mountain Research Station.

Franklin, S.E., R.J. Hall, L. Smith, and G.R. Gerylo (2003). Discrimination of conifer height, age and crown closure classes using Landsat-5 TM imagery in the Canadian Northwest. *International Journal of Remote Sensing*. 24(9):1823-1834.

Gessler, P.E., O.A. Chadwick, F. Chamran, L. Althouse, and K. Holmes (2000). Modeling soil-landscape and ecosystem properties using terrain attributes. Soil Science Society of America Journal 64:2046-2056

Helios Environmental Modeling Institute (HEMI) LLC (2000). The Solar Analyst 1.0 User Manual.

Hessburg, P.F., B.G. Smith, R.B. Salter, R.D. Ottmar, and E. Alvarado (2000). Recent changes (1930s-1990s) in spatial patterns if interior northwest forests, USA. *Forest Ecology and Management*. 136:53-83.

Joint Fire Science Program Modeling Project: Project Overview. 2003. Accessed April 27, 2004.
http://fire.org/nav.mas?pages=JFSP&mode=1

Keane, R.E.; S.A Mincemoyer, K.M. Schmidt, D.G. Long and J.L. Garner (2002). *Mapping vegetation and fuels for fire management on the Gila National Forest Complex, New Mexico*. General Technical Report. RMRS-GTR-46- CD. Ogden, UT: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. pp. 1-126.

Keane, R.E., R. Burgan, and J. van Wagtendok, (2001). Mapping wildland fuels for fire management across multiple scales: Integrating remote sensing, GIS, and biophysical modeling. *International Journal of Wildland Fire*. 10:301-319.

Kessell, S.R. (1979). *Gradient Modeling: resource and fire management*. Springer Verlag, New York, pp. 1-432. Lawrence, R.L. and A. Wright (2001). Rule-based Classification Systems Using Classification and Regression Tree (CART) Analysis. *Photogrammetric Engineering and Remote Sensing*. 67(10):1137-1142.

McBratney, A.B., M.L. Mendonc Santos, and B. Minasny (2003). *On digital soil mapping*. Geoderma. 117:3-52.

Miller, J.D., S.R. Danzer, J.M. Watts, S. Stone, and S.R. Yool (2003). Cluster analysis of structural stage classes to map wildland fuels in a Madrean ecosystem. *Journal of Environmental Management*. 68(3):239-252.

O'Hara, L.O., P.A. Latham, P. Hessburg, and B.G. Smith (1996). A Strctural Classification for Inland Northwest Forest Vegetation. *Western Journal of Applied Forestry*. 11(3):97-102.

Riano, D., E. Meier, B. Allgower, E. Chuvieco, and S.L. Ustin (2003). Modeling airborne laser scanning data for the spatial generation of critical forest parameters in fire behavior modeling. *Remote Sensing of Environment* 86:177-186.

Riano, D., E. Chuvieco, J. Salas, A. Palacios-Orueta, and A. Bastarrika (2002). Generation of fuel type maps from Landsat TM images and ancillary data in Mediterranean ecosystems. *Canadian Journal of Forest Resources*. 32:1301-1315.

Roberts, D., M. Gardner, J. Regelbrugge, D. Pedreros, and S. Ustin (1998). Mapping the distribution of wildfire fuels using AVIRIS in the Santa Monica Mountains. Available online: http://www.cstars.ucdavis .edu/papers/html/robertsetal1998c/index.html.

Rowan, L.C. and J.C. Mars (2003). Lithologic mapping in the Mountain Pass, California area using Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) data. *Remote Sensing of Environment*. 84:350-366.

Smith, A.J., P. Gessler, and D. Basford (2003). New vegetation mapping tools for the Salmon Challis National Forest. In: *ASPRS 2003 Conference Proceedings.*

Stage, A.R. (1973*). Prognosis model for stand development*. U.S. Department of Agriculture, Forest Service. INT-137, Intermountain Forest and Range Experiment Station, Ogden, Utah, pp.1-32.

Pocewicz, A., P.E. Gessler, and A.P. Robinson (In Press). The relationship between leaf area index and Landsat spectral response across elevation, solar insolation, and spatial scales, in a northern Idaho forest. *Canadian Journal of Forest Research*.

Pyne, S. J., P.L. Andrews, and R.D. Laven (1996). *Introduction to Wildland Fire*. John Wiley & Sons Inc., New York, pp. 1-769.

US Department of Agriculture (USDA) (2003). National Fire Plan: Managing the Impact of Wildfires on the Communities and Environment. Available online: http://www.fireplan.gov

Wilson, B. A., C.F.Y. OW, M. Heathcott, D. Milne, T.M. McCaffrey, G. Ghitter, and S.E. Franklin (1994). Landsat MSS classification of fire fuel types in Wood Buffalo National Park, Northern Canada. *Global Ecology and Biogeography Letter*. 4:33-39.

Zhu, G. and D.G. Blumberg (2001). Classification using ASTER data and SVM algorithms; The case study of Beer Sheva, Israel. *Remote sensing of Environment*. 80:233-240.