

Mapping surface fuel models using lidar and multispectral data fusion for fire behavior

Muge Mutlu^{a,*}, Sorin C. Popescu^a, Curt Stripling^b, Tom Spencer^b

^a Spatial Science Laboratory, Department of Forest Science, Texas A&M University, 1500 Research Parkway, Suite B221, College Station, TX 77843, United States

^b Texas Forest Service Forest Resource Protection, 301 Tarrow Suite 304, College Station, TX 11780, United States

Received 18 June 2006; received in revised form 1 May 2007; accepted 5 May 2007

Abstract

Wild-land fires have become intense and more frequent all over the world. Improving the accuracy of mapping fuel models is essential for fuel management decisions and explicit fire behavior prediction for real-time support of suppression tactics and logistics decisions. The overall aim of this paper is to develop the use of lidar (Light Detection and Ranging) remote sensing to accurately and effectively assess fuel models in East Texas. More specific goals include: (1) developing lidar derived products and the methodology to use them for assessing fuel models; (2) investigating the use of several techniques for data fusion of lidar and multispectral imagery for assessing fuel models; (3) investigating the gain in fuels mapping accuracy when using lidar as opposed to QuickBird imagery alone; and (4) producing spatially explicit digital fuel maps. Estimates of fuel models were compared with in-situ data collected over 62 plots. We employ a unique approach to classify fuel models using a combination of lidar height bins and multispectral image data. Different image processing approaches for fusing lidar and multispectral data, such as the Minimum Noise Fraction (MNF) and Principle Component Analysis (PCA), were used to improve the overall accuracy of image classification. Supervised image classification methods provided better accuracy (90.10%) with the fusion of airborne lidar data with QuickBird data than with QuickBird imagery alone (76.52%).

According to our results, lidar derived data provide accurate estimates of surface fuel parameters efficiently and accurately over extensive areas of forests. This study demonstrates the importance of using accurate maps of fuel models derived using new lidar remote sensing techniques.

© 2007 Elsevier Inc. All rights reserved.

Keywords: Lidar; Fuel models; Multispectral imagery; PCA; MNF; Height bins

1. Introduction

Wild-land fire is a critical issue around the world and fuel distribution, topography, wind, and fuel moisture are very important for defining fire behavior (Chuvieco & Congalton, 1989). Many forest fires occur each year and a huge amount of forest areas are lost in the United States. For example, in Texas alone, in 2005 there were a total of 2094 fires, which burned 54,148.96 ha (133,805 acres). It has been reported by the Texas

Forest Service (2006) that 88,086.71 ha (217,667 acres), more than the number of acres that burned in the entire year of 2005, have burned in Texas already in the first month, January, of 2006. To mitigate fire risks, land managers should identify those areas most in need of fuel mitigation efforts. Managing such risk is difficult since fuel hazards are changing, and because fire behavior is affected by many factors, including weather, wind conditions, and topography (Rome et al., 2006). Fire managers must provide more accurate fire behavior predictions, and there is a need to reflect on some factors such as canopy height, dead and live fuel load, and percent of canopy cover because these factors are known as fuel types (Pyne et al., 1996). Fire managers usually group vegetation communities into fuel types based on similar potential fire behavior (Riano et al., 2002). In addition, fuel models can be used to describe fuels (Anderson,

* Corresponding author. Tel.: +1 979 458 0742; fax: +1 979 862 2607.

E-mail addresses: mugemutlu@tamu.edu (M. Mutlu), s-popescu@tamu.edu (S.C. Popescu), cstripling@tfs.tamu.edu (C. Stripling), tspencer@tfs.tamu.edu (T. Spencer).

1982). A fuel type is an identifiable organization of fuel elements of an individual plant species, form, size, arrangement, or other characteristics that will cause a predictable rate of fire spread (Pyne et al., 1996). Fuel model refers to a combination of vegetation types for which all fuel descriptors required for the solution of a mathematical rate of spread model has been specified (Reeves, 1988). Fire risk depends on fuel properties, such as the quantity of biomass, the vertical and horizontal structure of the canopy, portion of live and dead biomass, and fuel moisture content (Pyne et al., 1996).

Fire managers recognize a total of three general types of wild-land fire: ground, surface, and crown fire. A ground fire burns in organic soils, roots, puff, muck, and peat (Scott & Reinhardt, 2001). Ground fires spread very slowly compared to surface and crown fires, but nevertheless, ground fires can be very destructive. A surface fire burns in the surface layer's leaves, short trees, grass, and branch wood (Scott & Reinhardt, 2001). A crown fire burns in the elevated canopy fuels. Canopy fuels normally consumed in crown fires consist of live and dead foliage (Scott & Reinhardt, 2001).

According to Anderson (1982), fuels have been classified into four groups: grasses, brush, timber, and slash. Fire behavior can differ if there is a direct relationship between the fuel load and its distribution among the fuel particle size classes (Anderson, 1982). A total of thirteen surface fuel models are identified for the United States, each varying in amount, size, and arrangement of the fuel model (Anderson, 1982). Fuel models are one of the inputs for fire simulation software, which help the user reasonably estimate fire behavior (Reeves, 1988) and they represent the fuel condition for a specific site (Rollins et al., 2004).

Remote sensing can support many aspects of fire management and it can be used to decrease fire risk and to reduce fire damage. In recent years, remote sensing techniques have been applied to estimate fuel models (Pyne et al., 1996). Baath et al. (2002) developed an approach to obtain practical information about recent and future forest fuel potentials. Airborne lidar (Light Detection and Ranging) systems have been used to estimate critical parameters for fire behavior and may, potentially, be used to compute and distinguish a range of fuel attributes including understory fuel height (Means, 2000; Roff et al., 2005). Detailed information can be extracted from lidar remote sensing such as accurate geometric X, Y, and Z position of reflecting surfaces which includes measurements of the forest canopy and ground surface (Lefsky & Cohen, 2002). Airborne lidar remote sensing is a powerful tool to obtain fuel information. Compared to traditional aerial photography or fieldwork, airborne scanning laser systems provide better spatial coverage and enough temporal resolution to update fuel maps (Riano et al., 2003).

Multispectral image classification is an important technique of remote sensing and image analysis. There are different ways to perform classification including supervised or unsupervised, parametric methods such as Maximum likelihood classification or nonparametric such as nearest-neighbor classifiers, and contextual or non-contextual algorithms (Jensen, 2005). Maximum Likelihood and Mahalanobis Distance that are sub-

classification methods of supervised image classification were used to determine which classifier is more efficient and useful for this study. To classify remotely sensed data successfully, supervised classification training sites must be carefully assigned to land-use and land-cover information (Congalton & Green, 1999; Lunetta et al., 1991).

The use of airborne lidar allows scientists to measure the three-dimensional structure of the canopy, and it also allows for more accurate and efficient estimation of canopy fuel characteristics over large areas of forests (Andersen et al., 2005). Lidar sensors are high resolution, active remote sensing tools that use lasers to measure the distance between the sensor and an object (Wagner et al., 2004). This technology is useful for obtaining accurate, high resolution measurements of surface elevations (Bufton et al., 1991). In addition, airborne lidar data can provide new information about the canopy surface and vegetation parameters such as height, stem density, crown dimensions, volume and biomass (Naesset & Okland, 2002; Nelson et al., 2003; Popescu et al., 2003, 2004). Operationally, lidar ranging data are commonly used for precise terrain elevation characterization.

There is a limited number of studies in the literature that used airborne scanning laser (lidar) systems to estimate forest fuel parameters. Riano et al. (2003) study has demonstrated that a semi-automated technique can be used to extract forest fuel distribution from lidar data in forests dominated by conifer and deciduous tree species. The results demonstrated that lidar can provide detailed spatial information on forest attributes relevant to fire behavior that may also be used for direct input into spatial fire behavior models. Morsdorf et al. (2004) used a *k*-means clustering algorithm to measure individual tree crown dimensions for forest fire risk assessment in Switzerland. In Andersen et al. (2005) study on regression analysis was used to develop predictive models relating a variety of lidar-based metrics to the canopy fuel parameters. The parameters were estimated from inventory data collected at plots established in stands of varying condition within Capitol State Forest, in western Washington State.

The overall aim of this paper is to develop a methodology to use lidar and multispectral remote sensing to accurately and effectively assess fuel models in East Texas. The specific objectives of this paper are to: (1) develop lidar-derived products and the methodology to use them for assessing fuel models; (2) investigate the use of several techniques for data fusion of lidar and multispectral imagery for assessing fuel models; (3) investigate the accuracy of fuel maps generated using lidar as opposed to the generation of fuel maps from satellite imagery alone; and (4) produce spatially explicit digital fuel maps.

2. Materials and methods

2.1. Study area

The study area is centered within the rectangle defined by 95° 24' 57" W–30° 39' 36" N and 95° 21' 33" W–30° 44' 12" N in east Texas near Huntsville. Forest stands are in various stages of development which include pine, pine-hardwood

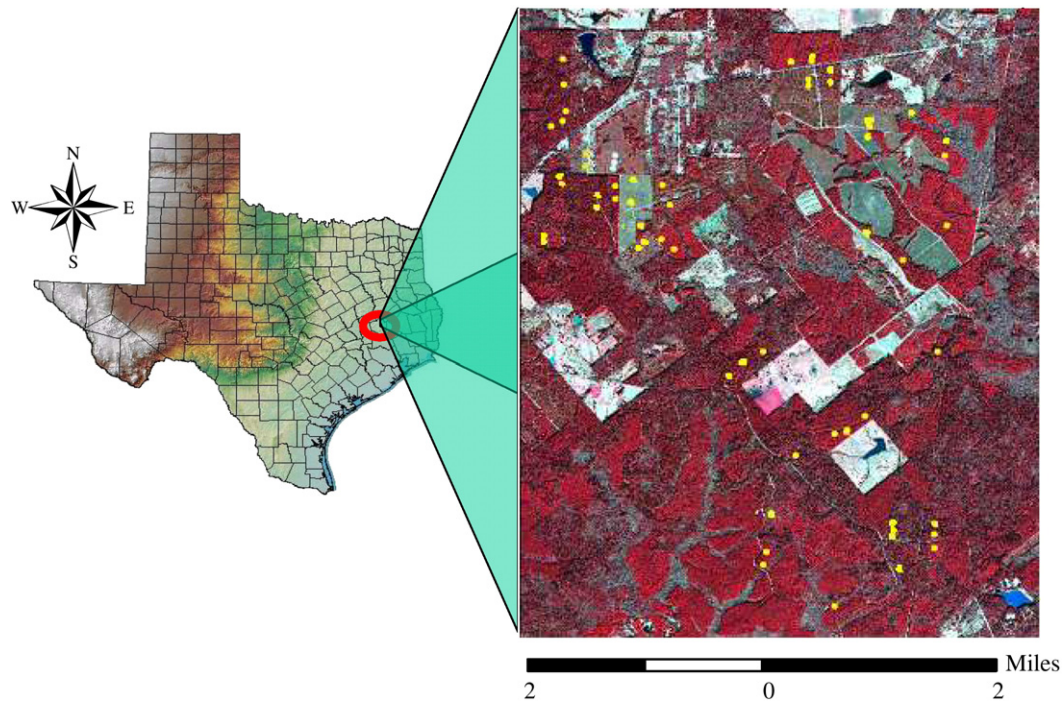


Fig. 1. Map of Texas indicating the location of our study area and false color composite of a QuickBird image, with field plot locations.

mixed stands, and hardwood stands in the study area. The study area also includes open ground with fuels consisting of grasses and brushes. Fig. 1 represents the QuickBird image, a high-resolution satellite owned and operated by DigitalGlobe with 2.5×2.5 m resolution, of the study area.

2.2. Data

Three types of data were used in this project: lidar data, in-situ data, and multispectral QuickBird data.

2.2.1. Lidar data

Lidar scanning data was provided by M7 Visual Intelligence Inc. in LAS format. The LAS file format is a binary file format that maintains information specific to the lidar nature of the data while not being overly complex (Graham, 2005). Lidar data were acquired over an area of 6474.9 ha (25 m^2) in leaf off condition during March 2004. A total of 47 flight lines were collected over the study area, with 28 flight lines obtained from East to West and 19 flight lines obtained from North to South. An average of 2.58 points/ m^2 and a max of 39.84 points/ m^2 were found. The wide range of point density is due to areas with four overlapping flight lines, east to west and north to south. Fig. 2 shows the flight lines over the study area. This flight line arrangement with complete lidar coverage from two different directions was designed to allow a good penetration of laser shots to determine the ground for characterizing surface fuels and to reduce effects of row direction on pine plantations.

2.2.2. Ground inventory data

In order to assess fuel models and forest inventory parameters and determine the accuracy of airborne lidar estimates,

in-situ data were gathered for this study from May 2004 to July 2004. A total of 62 plots including a total of 1005 trees were measured in the study area. Potential plot locations were initially identified using ground reconnaissance to ensure adequate sampling of the common fuel types in east Texas. This strategy was used due to the difficulty of identifying fuels based solely on Quickbird satellite imagery. After several

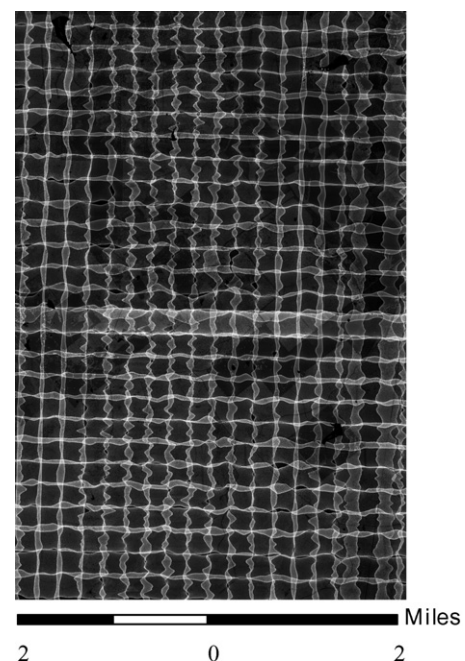


Fig. 2. Flight lines over the study area.

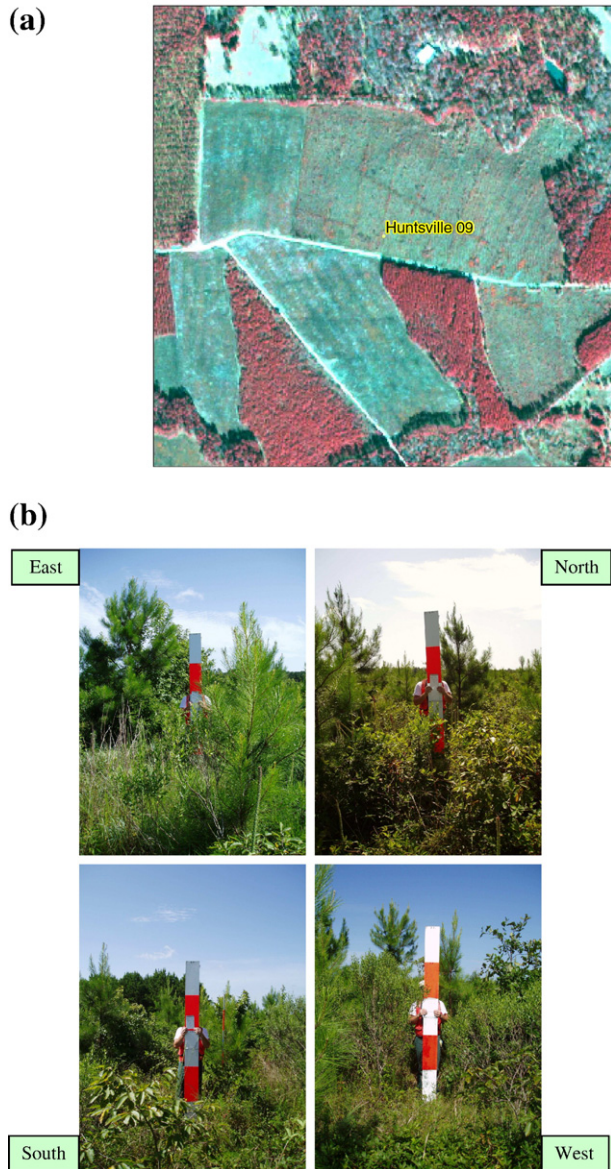


Fig. 3. (a) Location of Plot #8 in the study area shown on the QuickBird image, (b) digital photos of Plot #8.

potential sites were located on the ground, random plot locations within these stands were generated in the office.

A 404.7 m² (1/10th acre) circular plot with a radius of 11.35 m (37.24 ft) was established for all forested and non-forested plots, except for the ones located in unthinned pine plantations. Because of the uniformity of trees in unthinned plantations, a smaller plot size of 40.468 m² (1/100-acre) with a radius of 3.59 m (11.78 ft) was used.

Plots were located in the field by obtaining a distance and direction from an identifiable feature on the Quickbird imagery and using a compass to chain in. This method was preferred over GPS navigation because of poor GPS satellite reception underneath the forest canopy. To prevent bias, the data collector used the predetermined distance and direction to the establish plot center. Once the plot center was established, the coordinates were recorded with a GeoExplorerXT. A minimum of 30 posi-

tions were collected for each plot and saved to the GeoExplorerXT unit, so they could be differentially corrected later using Trimble's Pathfinder software and CORS stations data (Continuously Operating Reference Stations – National Geodetic Survey). In order to receive an adequate GPS signal, we raised the antenna height between 3.66 m (12 ft) to 4.88 m (16 ft).

All trees were measured and species were identified within the plot boundaries. Each tree location was mapped using distance and azimuth from plot center. Tree distance was measured to the nearest 3 cm (0.1 ft) using a Haglöf Vertex III Hypsometer and azimuth was measured to the nearest degree. The tree height and crown base height were also measured with a Haglöf Vertex III Hypsometer to the nearest 3 cm (0.1 ft). Crown base height was determined by the first live branch or whorl. DBH was measured to nearest 0.25 cm (0.1 in.) and crown diameter was measured to the nearest 3 cm (0.1 ft) in a north to south and east to west direction. Tree crowns were classified based on the Kraft system such as dominant, co-dominant, intermediate, and suppressed. In addition to the tree measurements, information was collected on understory vegetation and ground cover.

Fuel models can be quickly estimated by taking a photo series including detailed data for each fuel complex shown (Reeves, 1988). Six digital photographs were taken from each plot center, with two photos taken from a general view and four photos taken facing north, south, east, and west directions. Fig. 3 (a) represents the location of Plot #8 in the study area and Fig. 3 (b) represents the digital photos that are taken from the plot center facing north, south, east, and west. These photos were then evaluated to assess fuel models (Anderson, 1982; Reeves, 1988).

A total of seven fuel models were identified in our study area: Fuel model 1, Fuel model 2, Fuel model 4, Fuel model 5, Fuel model 7, Fuel model 8, and Fuel model 9. Table 1 presents

Table 1
Description of fuel models

Fuel Model (FM)	Summary from Anderson (1982)
Grass and grass dominated	
FM#1 — Short Grass (0.30 m)	Short lived and dead grass, grass-tundra, grass-shrub combinations (1/3 brush)
FM#2 — Timber (grass-understory)	Open shrub lands and pine or scrub oak stands which cover 1/3 to 2/3 of the area.
Chaparral and shrub fields	
FM#4 — Chaparral (1.82 m)	Stands of mature shrubs 1.82 m or more, live and dead fine woody material in the crowns of a nearly continuous secondary overstory.
FM#5 — Brush (0.60 m)	Young and short shrubs, little dead material, and grasses, in the understory, light surface fuel loads
FM#7 — Southern rough	Stands of shrubs between 0.60 m and 1.82 m high, Palmetto-gallberry understory-pine overstory sites, occasionally black spruce-shrub combination
Timber litter	
FM#8 — Closed timber litter	Closed canopy stands of short-needle conifers or hardwoods. Needles, leaves, and occasionally twigs in the understory
FM#9 — Hardwood litter	Long-needle conifer and hardwood stands, closed stands of long-needled pine like ponderosa, Jeffrey, red pines, and southern pine plantations.

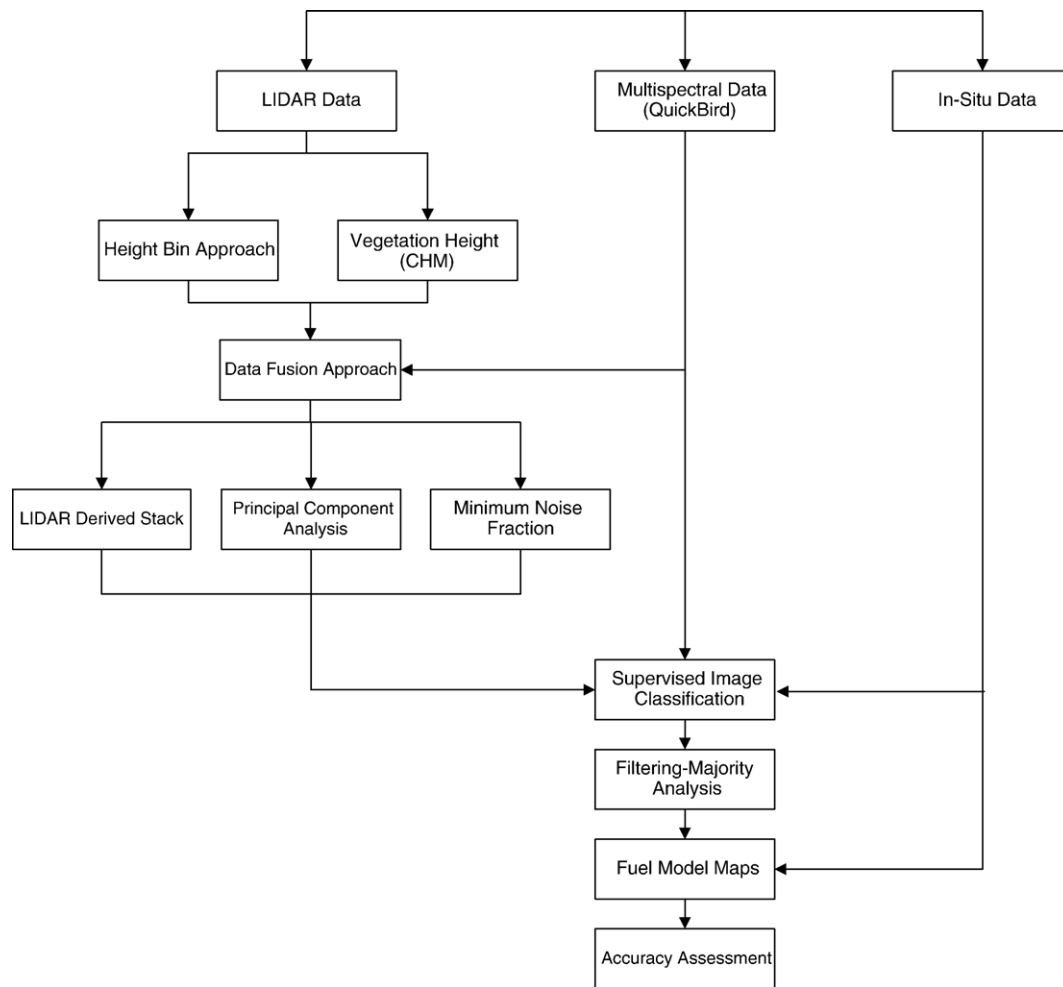


Fig. 4. Flow chart of processing approach.

the description of each fuel model summarized from [Anderson \(1982\)](#).

Each plot fuel model type was determined by the authors and specialists from Texas Forest Service personnel involved with fire behavior and mitigation efforts, in a joint meeting. Each of the six digital photographs available for each plot, as well as field inventory data, were analyzed to determine fuel models by using recorded field data, knowledge of local fuel models, and

fuel models descriptions in [Anderson's \(1982\)](#) study. Field surveys and digital photographs analysis can easily differentiate between fuel models 1, 2, and 4. Fuel model 1 consists of short grasses without tree cover; fuel model 2 is made of shrubs under 1/3 to 2/3 canopy overstory, while fuel model 4 contains mainly brushes without canopy cover. Confusion could occur between fuel models 5 and 7, which are both brush models under the canopy cover. The difference between fuel models 5 and 7 lies

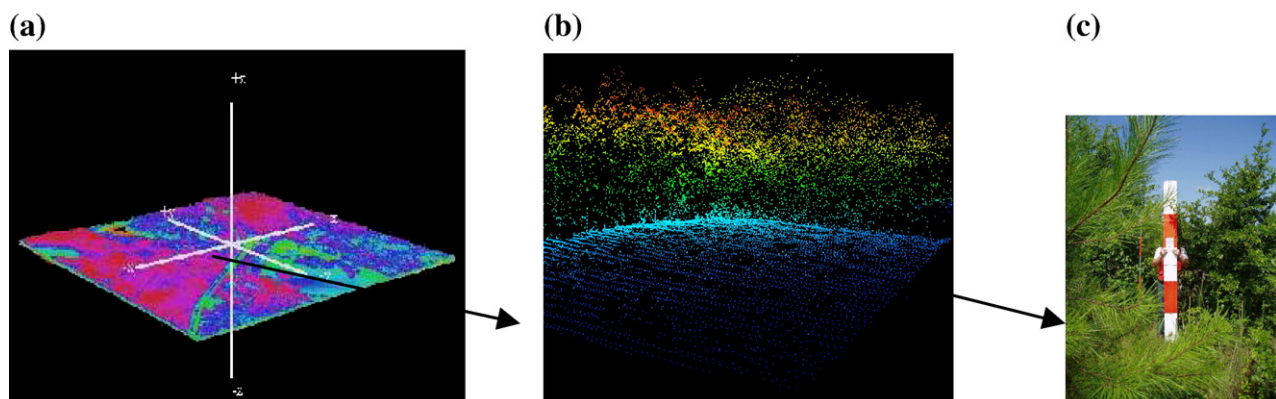


Fig. 5. (a) The 3D of laser hits of Plot 9, (b) zoom in view of Plot 9, and (c) the digital photograph from the area.

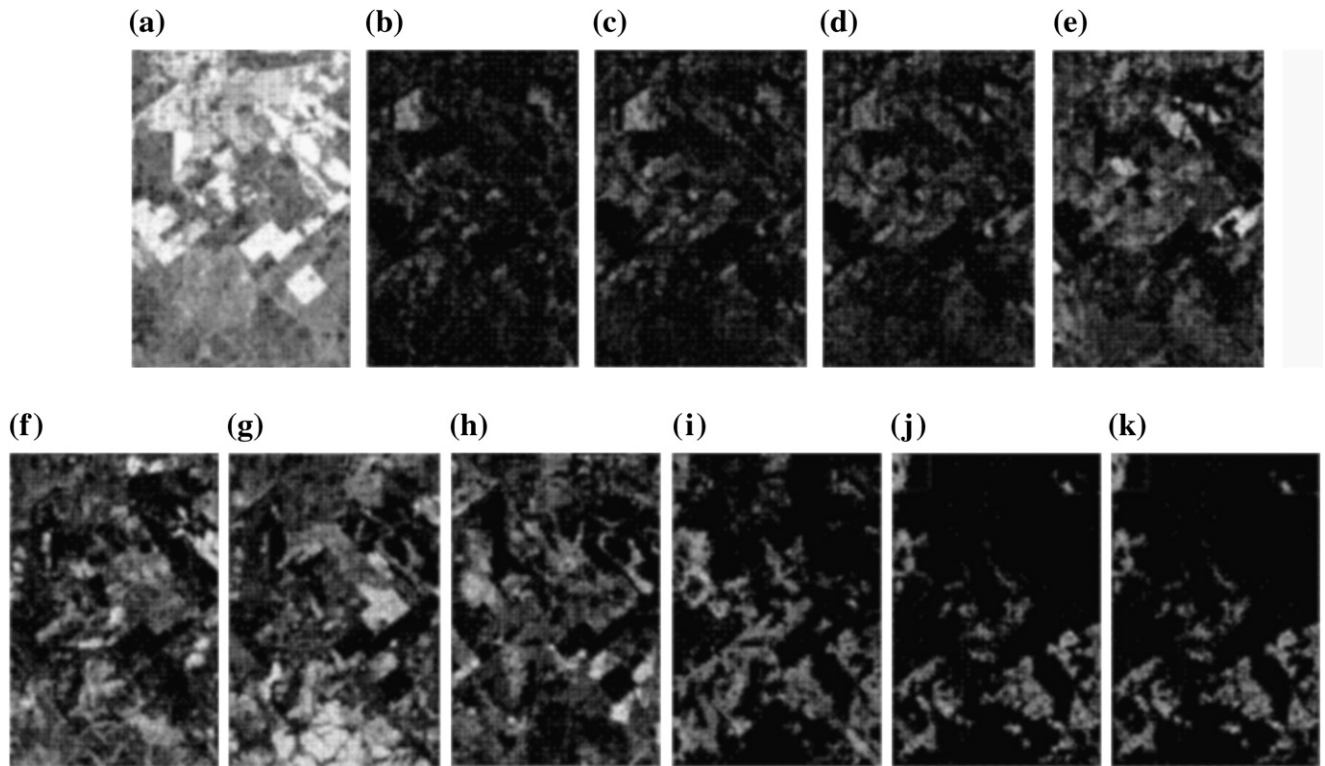


Fig. 6. Overall view of the eleven Height Bins. (a) Bin 1: 0–0.5 ft, (b) Bin 2: 0.5–1.0 ft, (c) Bin 3: 1.0–1.5 ft, (d) Bin 4: 1.5–2.0 ft, (e) Bin 5: 2.0–2.5 ft, (f) Bin 6: 2.5–5.0 ft, (g) Bin 7: 5.0–10.0 ft, (h) Bin 8: 10.0–15.0 ft, (i) Bin 9: 15.0–20.0 ft, (j) Bin 10: 20.0–25.0 ft, (k) Bin 11: >30.0 ft.

mainly in their height; therefore, we expect lidar data to contribute to the differentiation between these fuel models. For fuel model 5, brush height is up to 0.60 m, while for fuel model 7, brush height is between 0.60 and 1.82 m.

Careful consideration should be given when differentiating between fuel models 7, 8, and 9. Fuel model 7, also known as Southern Rough, is defined by shrubs with heights between 0.60 m and 1.82 m, under pine overstory. Although the overstory can be characterized as closed canopy, shrubs in fuel model 7 need a more open canopy to develop up to 1.82 m height, as compared to fuel models 8 and 9. Fuel models 8 and 9 develop under closed canopy stands. The main difference between fuel models 8 and 9 is that fuel model 8 contents mainly

short-needle conifers or hardwoods, tightly compacted, while fuel model 9 contains more porous long-needles and hardwood litter and, in Texas, occurs mainly under pines.

2.3. Processing approach

The overall study steps to derive fuel maps are illustrated in Fig. 4.

2.3.1. Height bins approach

The height bin approach was used to generate a lidar-derived multiband data set from scanning data, with each band corresponding to a height bin. The height bins approach makes use

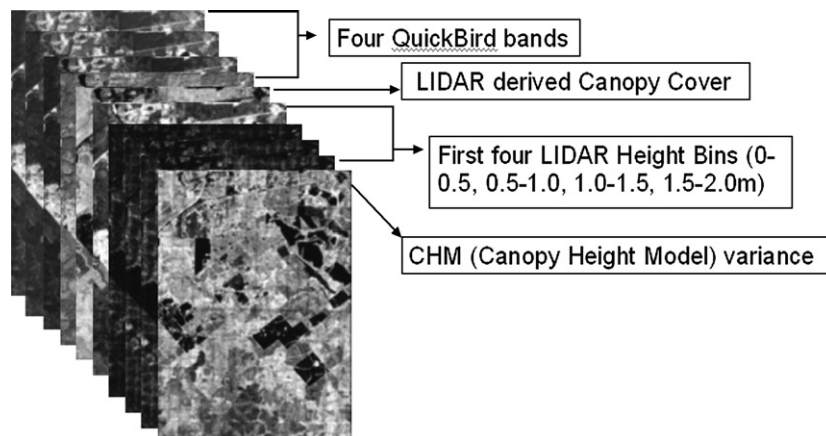


Fig. 7. The lidar-QuickBird stack image.

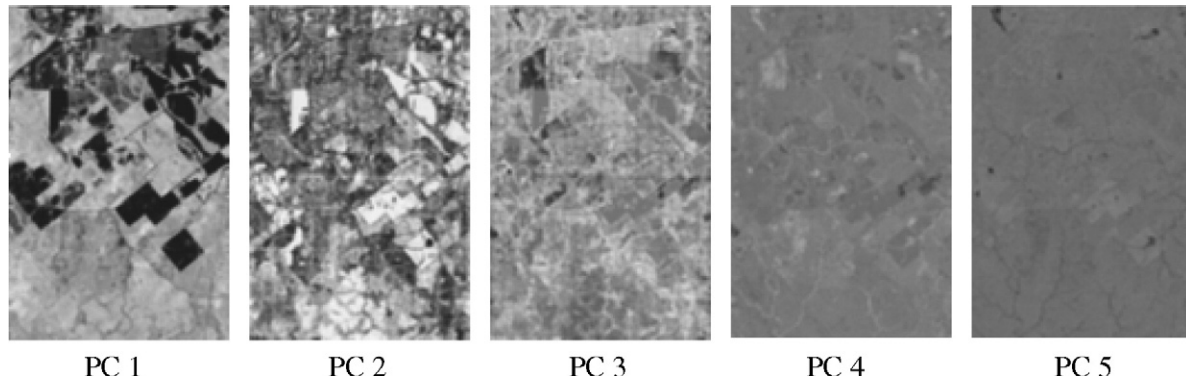


Fig. 8. First five PC images.

of the entire lidar point cloud. Lidar bins were created by counting the occurrence number of lidar points within each volume unit and normalizing by the total number of points. Since the lidar point density varies spatially, normalizing by the total number of points over a given pixel eliminates the effects of variable point density. The percentage of lidar hits can be obtained for any height interval. Fig. 5(a) represents 3D distribution of laser hits of Plot 9, Fig. 5(b) shows the zoom in view of Plot 9, and Fig. 5(c) represents the digital photograph that was taken from the area. A total of eleven lidar height bins were obtained and Fig. 6 illustrates the output of this process. The first four height bins are generated for 0.5 m height intervals to afford a better characterization of vegetation that defines surface fuels. The upper bins are spaced at 3 m and 5 m, band 6 to 10. The last bin is generated from laser hits above 30 m.

We chose to use a horizontal spatial resolution of 2.5 m for our lidar height bins. For an average point density of 2.58 points/m², on average there are 16.125 lidar points for each 2.5 × 2.5 m cells to characterize the vertical distribution of intercepting vegetation surfaces. The horizontal spatial resolution matches well with the QuickBird satellite imagery spatial resolution, resampled from 2.4 m to 2.5 m.

2.3.2. Data fusion approach

Data fusion deals with association, correlation, and combination of information and data from one or many sources (Llinas, 2002). In this study, three different data fusion approaches were used: lidar-multispectral stack, principal component analysis, and minimum noise fraction (MNF). A new image, lidar-QuickBird stack image of ten bands, was created by stacking the four bands of the QuickBird image with four lidar height bins, three lidar-derived bands, one band from the canopy cover model, and one band from the canopy cover variance. Principal Component Analysis (PCA) is a helpful statistical technique that is used to produce uncorrelated output bands, to segregate noise components, and to reduce the dimensionality of data sets (Jensen, 2005). The MNF transform is used to determine the inherent dimensionality of image data, to segregate noise in the data, and to reduce the computational requirements for subsequent processing (Boardman & Kruse, 1994). The MNF method is similar to PCA that has been used

for a long time in multispectral image processing. We investigated both principal components and minimum noise fraction to create new fused images. We then applied supervised image classification on the new images, examined its effect for improving overall classification accuracy, and finally compared results.

2.3.2.1. Lidar-derived Stack. By using ENVI 4.2 (Research Systems, Inc.) we built a new multiband image with 2.5 m spatial resolution. This image includes a total of 10 bands and will be subsequently referred to as the lidar-QuickBird Stack. As is shown in Fig. 7, the first four bands are taken from the Quickbird image, the fifth band is lidar derived canopy cover, sixth, seventh, eighth, and ninth bands are obtained from the first four lidar height bins (0–0.5, 0.5–1.0, 1.0–1.5, 1.5–2.0 m), and the last band is obtained from canopy height model variance. We used only the first four lidar bins by assuming they characterize best the vertical structure of surface fuels within a 2 m vertical canopy space adjacent to the ground.

2.3.2.2. Principal Component Analysis (PCA). PCA was applied to the lidar-QuickBird stack image, which has ten bands. We used the first five of the ten PCs for our subsequent image classification. Fig. 8 illustrates the first five PCs. The PCA transformation is based on the variance and covariance of the data set (Smith, 2002). Eigenvalues, variance, and eigenvector were extracted for each PC. Table 2 represents the percentage of total variance, eigenvalues, and cumulative variance explained by each principal component. The first principal component accounts for 88.97% of variance in the entire lidar and multispectral data set. In addition, the first five components that we used for image classification account for approximately 99% of the total variance. It can be concluded that the first five

Table 2

Calculations of eigenvalues, percentage of total variance and cumulative percentages for each PCs

PCs	Eigenvalue	% of total variance	Cumulative
PC1	873,676.7	88.97	88.97
PC2	53,848.92	5.48	94.46
PC3	31,214.62	3.17	97.63
PC4	7711.736	0.78	98.42
PC5	6495.253	0.66	99.08

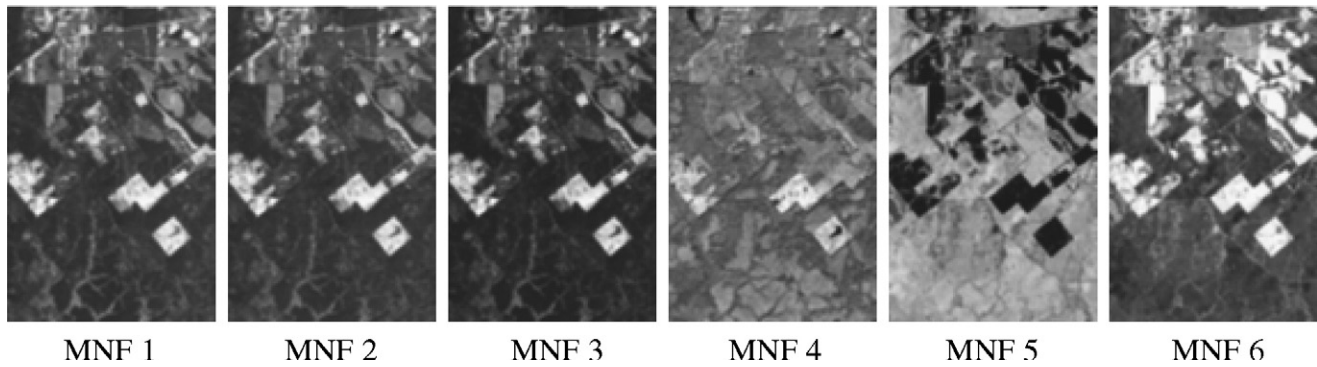


Fig. 9. MNF images.

principal components can replace the original ten bands of the lidar-QuickBird stack image, while reducing the size of the data set, redundancy, and noise.

2.3.2.3. Minimum Noise Fraction (MNF). MNF was applied to the lidar-QuickBird stack image that has ten bands. MNF determines the dimensionality of image data, separates noise in the data, and reduces the computational requirements for processing (Boardman & Kruse, 1994). The MNF transform basically consists in two coupled Principal Components transformations (Green et al., 1988). The first transformation is based on an estimated noise covariance matrix; it rescales and decorrelates any noise in the data. This first step results in transformed data in which the noise has unit variance and no band-to-band correlations. Principal components transformation is the second step that creates new bands containing the majority of the information. By examination of the eigenvalues, the inherent dimensionality of an image can be determined, thus allowing further spectral processing. Data is typically separated into one part with coherent eigenimages with large eigenvalues and into another apart with an abundance of noise and eigenvalues closer to one (ENVI, 2003). Six of the ten MNF bands were stacked, and each band is shown in Fig. 9. Eigenvalues, percentage of variance, and cumulative variance were calculated for each MNF band as is shown in Table 3. The table shows that the first six MNF bands account for approximately 97% of the total variance. As such, we decided to use the first six components of the MNF band transformed image for our subsequent processing.

2.3.3. Image processing

The first step in undertaking a supervised classification is to define the areas that will be used as training sites for each fuel

model class. Seven initial classes were considered and classification accuracy was evaluated using confusion matrixes and K-hat statistics. The Region of Interest (ROI) actually corresponds to our field plots. A plot of 11-m radius covers approximately 80 pixels, given a 2.5 m spatial resolution for our data. Thus, the 80 pixel-size resulted from collecting a circular shaped ROI over the field plot. A total of twenty-seven polygons were selected for the image classification training data set. The training data set results in a total of 2160 pixels for each of the QuickBird image, lidar-QuickBird stack image, principal component image, and minimum noise fraction image. Then, ROI separability reports, which calculate the spectral separability between chosen ROI pairs for a given input file (Jensen, 2005), have been computed for each data set. The same ROIs chosen over the lidar-QuickBird stack image were used on the stack of first five PCs and stack of first six MNF component images.

Supervised image classification was performed using parametric decision rules, such as the Maximum Likelihood and the Mahalanobis Distance decision rules with the multispectral QuickBird image, the lidar-QuickBird stack image, the principal component image, and the minimum noise fraction image. Image classification results in a per pixel characterization of fuels. A total of twenty-four field plots provided the accuracy assessment training data set, each plot with 80 pixels. According to Jensen (2005, p. 350), the training data set is of value if the environment from which they were collected is relatively homogeneous. As such, eleven field plots were not used for either the training or the accuracy data sets; these plots were located in young pine plantations that included a mixture of fuel models with rows of young pines and grass. Since we evaluated fuel models on a per plot basis, we applied a majority filter to the classified image using a 7×7 window size. We assessed the accuracy of this final map of fuel models for each data set. The Kappa statistic (K-hat) derived for each classification verifies if classification results are precise (Congalton and Green, 1999; Jensen, 1996; Lillesand and Kiefer, 1994).

3. Results and discussion

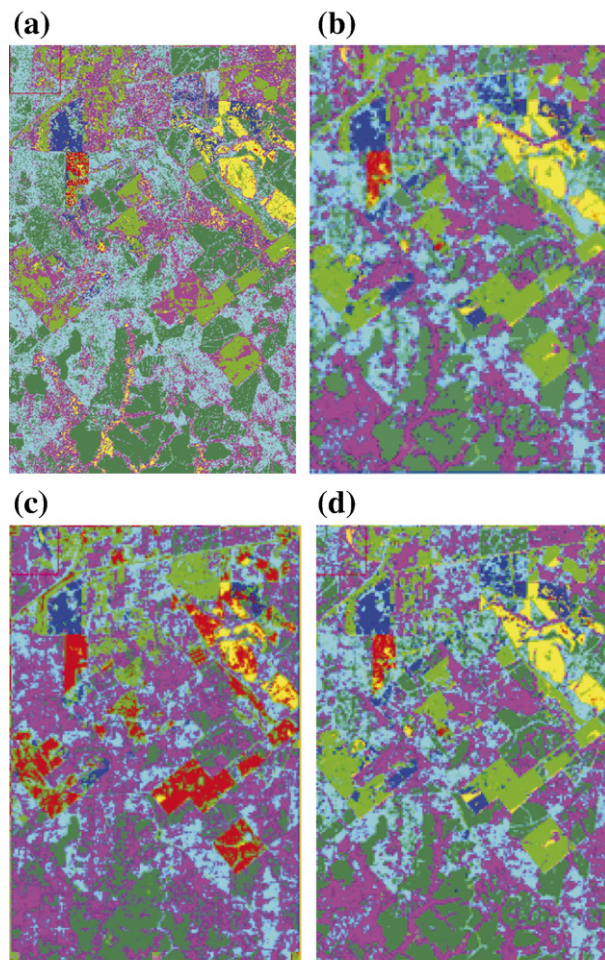
The results of four classification methods and classification accuracies were assessed. Among all the supervised image classifications that we applied to our images, Maximum

Table 3
Calculations of eigenvalues, percentage of total variance and cumulative percentage for each MNF components.

MNF	Eigenvalue	% of total VAR	Cumulative
MNF1	183.95	83.33	83.33
MNF2	17.14	7.76	91.10
MNF3	5.33	2.41	93.52
MNF4	4.01	1.81	95.34
MNF5	3.02	1.36	96.71
MNF6	2.01	0.91	97.62

Likelihood yielded the best results for the multispectral QuickBird image with 76.52% overall accuracy and 0.68 kappa coefficient. Mahalanobis Distance yielded the best results for the lidar-QuickBird stack image with 87.17% overall accuracy and 0.83 Kappa Coefficient. Fig. 10(a) represents the result of multispectral QuickBird image classification; Fig. 10(b) illustrates the result of the lidar-QuickBird stack image.

With the PC image, the Mahalanobis Distance classifier provided the best results. The accuracy assessment was 62.44% and the Kappa Coefficient was 0.53. Compared to the accuracy of the multispectral QuickBird and lidar-QuickBird stack images, the PC stack image was less accurate. Fig. 10(c) represents the output of the PC stack image.



F-M # 1	Grass
F-M # 2	Grass
F-M # 4	Brush
F-M # 5	Brush
F-M # 7	Brush
F-M # 8	Timber
F-M # 9	Timber

Legend for all classifications

Table 4

Comparison of results for all supervised image classification algorithms

	Overall accuracy (%)	Kappa coefficient
Multispectral QuickBird Image	76.52	0.68
Lidar-QuickBird Stack Image	87.17	0.83
PC stack image	61.46	0.52
MNF stack image	90.10	0.86

As for the MNF image, the Mahalanobis Distance decision rules classification yielded the best results of all the supervised image classification decision rules with an accuracy assessment of 90.10% and with a Kappa Coefficient of 0.86 for a new MNF image. Fig. 10(d) illustrates the output of this classification process and Table 4 shows a comparison of results for all supervised image classifications. Compared to the multispectral QuickBird image, lidar-QuickBird stack, and PC stack images accuracy, MNF provided the best result by having the highest accuracy.

Both Maximum Likelihood and Mahalanobis Distance classifiers are parametric methods. Despite the significant improvement of the overall accuracy provided by the Mahalanobis Distance classifier, with all of our input images, we cannot conclude that the latter would always provide better results when classifying surface fuel models with a data fusion approach similar to the one used in our study. The Mahalanobis Distance decision rule assumes all class covariances are equal. The advantage of the Mahalanobis classifier over the Maximum Likelihood decision rule is that it is faster (Richards & Jia, 2006), and therefore, may be more appropriate for larger area projects. The Maximum Likelihood classifier, although a powerful classification method, it is more sensitive than most other supervised techniques to variations in the quality of training data (Campbell, 2006). As such, given our larger plot size of 404.7 m² and the fact that surface fuels may vary within the plot, Maximum Likelihood provided a lower classification accuracy than the Mahalanobis classifier. One can only investigate what classifier works best for a given set of fuels, forest vegetation type and condition, and remote sensing data characteristics.

In areas with very dense overstory, the density of lidar returns near the ground will be much lower, regardless of the surface fuel density. Nevertheless, the vertical distribution of the lidar point cloud above such areas, which is characterized by the vertical profile of the height bins, will depict the canopy conditions that are specific for a certain type of fuel model. In other words, someone should not expect lidar points to always sample directly the fuel model on the ground, but to describe the overall forest canopy condition that is conducive to the development of a specific fuel model. This is mostly the case with fuel models 7, 8, and 9, respectively brush under the canopy, closed timber litter, and hardwood litter. We would not expect the lidar hits to characterize directly the tightly compacted dead foliage, typical for fuel model 8, or the deeper, more porous litter that makes fuel model 9, both occurring under dense canopy. However, fuel model 8 typically occurs in Texas under bottomland hardwoods, while fuel model 9 is more often found under pines canopy. With a leaf-off lidar data set,

Fig. 10. (a) The classification result of multispectral QuickBird image, (b) the classification result of data fusion stack of lidar and multispectral imagery, and (c) The classification result of PC stack image, (d) The classification result of MNF stack image.

Table 5
The average height bin values for every fuel model

Fuel Model	Lidar height bins			
	0–0.5 m	0.5–1.0 m	1.0–1.5 m	1.5–2.0 m
1	0.985	0.003	0.002	0
2	0.87	0.005	0.003	0.003
4	0.816	0.032	0.035	0.024
5	0.976	0.005	0.003	0.001
7	0.423	0.02	0.025	0.024
8	0.309	0.01	0.015	0.018
9	0.302	0.007	0.01	0.011

the first four height bins are expected to depict differences in canopy structure and penetration, although closed canopy, that lead to the development of these separate fuel models. The other fuel models, grasses, chaparral, and brush, intercept most of the lidar hits when the canopy is open or not present at all, therefore lidar height bins directly measure and characterize these fuels, not canopy parameters favorable to the development of fuel models, as in the case of fuel models 7, 8, and 9. To illustrate this aspect, for the best overall classification indicated by the accuracy assessment results, i.e., Mahalanobis distance applied to the MNF fused data set, we calculated the average height bin values for every fuel model present in the classified image (Table 5).

Fig. 11 shows the average height bin values for the first four bins, with different y-axis scales for each height bin to better depict the differences between fuel models in each height bin. Fig. 11 clearly shows the difference between fuel models as depicted by lidar. For the grass fuel models 1, 2, and brush fuel model 4, graphs are self explanatory. Grass fuel models display higher bin values for height bin 1 and close to null values in the higher bins. The brush fuel model (4) developing without

overstory shows high pixel values in all four height bins. For fuel models 5 and 7, which are both brush under the canopy, but of different height — fuel model 5 has brush up to about 0.60 m, while fuel model 7, between 0.60 and 1.82 m, differences depicted by height bins are obvious. Evidently, multispectral imagery alone would have difficulties when differentiating between these two brush models. Differences are evident between fuel models 7, 8, and 9, which occur under close canopy. For example, fuel model 7 with brush up to 1.82 m, shows more lidar hits in all four height bins, than fuel model 8 and 9, which mainly consist of litter. As anticipated earlier in Section 2.2.2, differences between timber fuel models 8 and 9 may not be the result of lidar intercepting directly the surface fuels, due to issues with lidar occlusion by the close canopy overstory. However, lidar is expected to depict differences in the overall canopy structure, with different penetration characteristics, that favors the development of one or the other fuel models. Based on our results, it appears that fuel model 8 develops when there is more lidar penetration down to heights of 0.5 to 2.0 m. Statistical pattern recognition methods exploit such differences and categorize pixels in the image data set into the fuel model class it most closely resembles, as indicated by the fuel models training data set.

4. Conclusion

Results from this study indicate that lidar can be used to generate accurate estimates of surface fuel models efficiently and accurately over extensive areas of forests. Lidar derived products were able to assess fuel models with high accuracy. Innovative methods for fusing airborne lidar and satellite imagery (QuickBird) were developed, which resulted in increased accuracy for classification of surface fuels. The

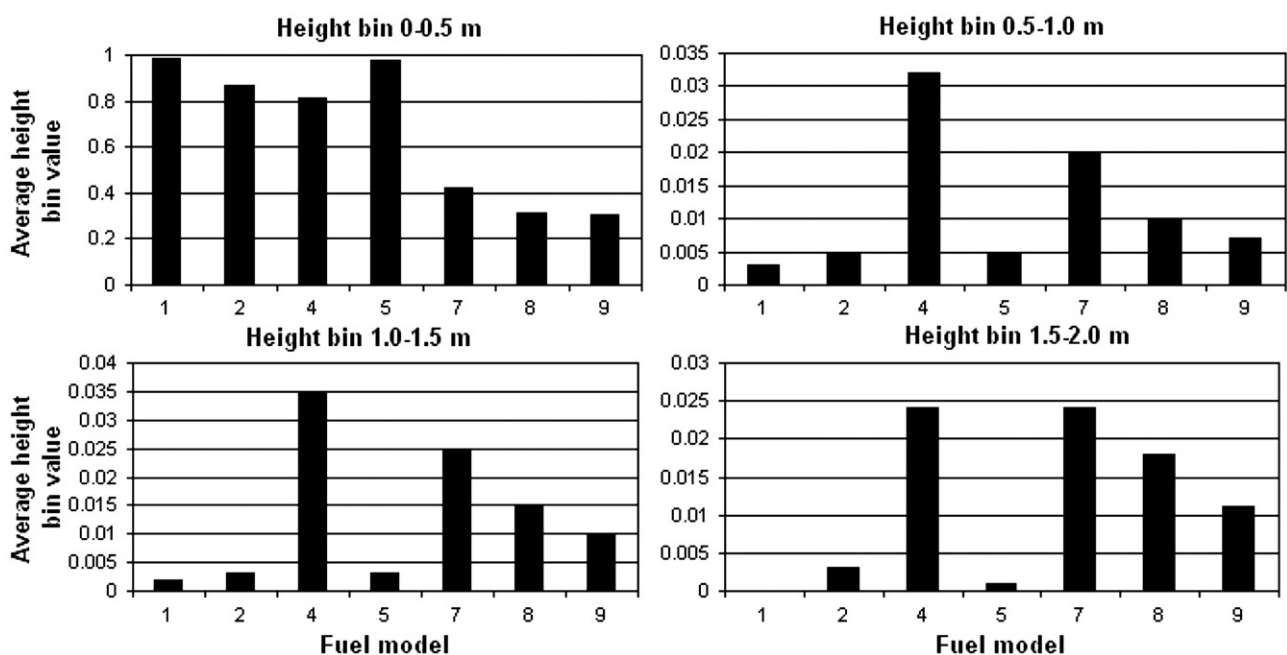


Fig. 11. The average height bin values for the first four bins.

Maximum Likelihood and Mahalanobis Distance supervised image classifications were effective in this study. The method that we developed by using lidar height bins fused with multispectral data has great potential for becoming a standard approach for mapping fuels with lidar and multispectral imagery. PCA did not provide improved results, with an accuracy of 62.44. Compared to the multispectral Quickbird image classification, the MNF stack image, which has lidar-derived components, increased the overall accuracy by 13.58%. The data fusion approach, combining lidar and multispectral QuickBird imagery, improves the overall accuracy of image classification of fuels. This study achieved a detailed mapping of fuels for input into fire behavior models such as FARSITE and FlamMap. Many fire managers do not have the fuel maps needed to run the fire simulation models for their area. We developed this spatial data layer using a unique remote sensing approach that fuses innovative lidar-derived products and multispectral imagery. Fuel models are just one way of assessing fire behavior. In addition to fuel models, there are other physical properties used as input to fire behavior models such as FARSITE, e.g. terrain height, crown base height or vegetation cover. These inputs are just as important as fuel models and need to be assessed in a dedicated way. A future study will analyze the influence of a more accurate fuel map on modeling fire behavior and assessing fire risk. Resulting remote sensing methods and mapping products have the potential for driving changes in forest resource management practices related to mitigating fire hazard that threatens the public, human lives, and environmental health in Texas and nationwide. Our results could significantly impact forest policy and forest resource management.

References

- Andersen, E. H., McGaughey, J. R., & Reutebuch, E. S. (2005). Estimating forest canopy fuel parameters using lidar data. *Remote sensing of Environment*, 94, 441–449.
- Anderson, H. E. (1982). *Aids to determining fuel models for estimating fire behavior*. USDA, Forest Service, General Technical Report INT-122 Ogden, UT: Intermountain forest and range Experiment Station, 4–16 pp.
- Baath, H., Gallerspang, A., Hallyby, G., Lundstrom, A., Lofgren, P., Nilsson, M., et al. (2002). Remote sensing, field survey and long-term forecasting: An efficient combination for local assessments of forest fuels. *Biomass and Bioenergy*, 22(3), 145–157.
- Boardman, J. W., & Kruse, F. A. (1994). Automated spectral analysis: A geological example using AVIRIS data, North Grapevine Mountains, Nevada. *ERIM 10th thematic conference on geologic remote sensing* (pp. I-407–I-418). Environmental Research Institute of Michigan Ann Arbor, MI. Springer Netherlands.
- Bufton, J. L., Garvin, B., Cavanaugh, J. F., Ramos-Izquierdo, L., Clem, T. D., & Karabill, W. B. (1991). Airborne lidar for profiling of surface topography. *Optical Engineering*, 30, 72–78.
- Campbell, J. B. (2006). *Introduction to remote sensing*, (4th ed.). New Jersey: Prentice–Hall Inc. 343 pp.
- Chuvieco, E., & Congalton, R. G. (1989). Application of remote sensing and geographic information systems to forest fire hazard mapping. *Remote sensing of Environment*, 29, 147–159.
- Congalton, R. G., & Green, K. (1999). Assessing the accuracy of remotely sensed data. *Principles and practices*, vol. 65 (pp. 1–137). Boca Raton FL: Lewis Publishers.
- ENVI. (2003). *Environment for Visualizing Images (ENVI)*. User's guide, version 4.0. Boulder, CO: Research System Inc. 645–647 pp.
- Graham, L. (2005). The LAS 1.1. Standard. *Photogrammetric Engineering & Remote Sensing*, 71(7), 777–780.
- Green, A. A., Berman, M., Switzer, P., & Craig, M. D. (1988). A transformation for ordering multispectral data in terms of image quality with implications for noise removal. *IEEE Transactions on Geoscience and Remote Sensing*, 26(1), 65–74.
- Jensen, J. R. (1996). *Introductory digital image processing: A remote sensing perspective*, 2nd edition. Upper Saddle River, NJ: Prentice–Hall Inc. 78–81 pp.
- Jensen, J. R. (2005). *Introductory digital image processing: A remote sensing perspective*, (3rd ed.). New Jersey: Prentice–Hall Inc. 114–116 pp.
- Lefsky, M. A., Cohen, W. B., Parker, G. G., & Harding, D. J. (2002). Lidar remote sensing for ecosystem studies. *Bioscience*, 52(1), 19–30.
- Lillesand, T. M., & Kiefer, R. W. (1994). *Remote sensing and image interpretation* (3rd ed.). New York: Wiley. 585–618 pp.
- Llinas, J., (2002). Center for multisource information fusion university at Buffalo, Buffalo, NY. Online at: <http://www.infofusion.buffalo.edu/tm/Dr.Llinas/stuff/DataFusionOverview.ppt#1>
- Lunetta, R. S., Congalton, R. G., Fenstermaker, L. K., Jensen, J. R., McGwire, K. C., & Tinney, L. R. (1991). Remote sensing and geographic information system data integration: Error sources and research issues. *Photogrammetric Engineering & Remote Sensing*, 57(6), 677–687.
- Means, J. E. (2000). Comparison of large-footprint and small-footprint lidar systems: Design, capabilities, and uses. *2nd international conference on geospatial information in agriculture and forestry*, Lake Buena Vista, Florida, 10–12. 185–192.
- Morsdorf, F., Meier, E., Kötz, B., Itten, K. I., Dobbertin, M., & Allgöwer, B. (2004). Lidar-based geometric reconstruction of boreal type forest stands at single tree level for forest and wild land fire management. *Remote Sensing of Environment*, 92(3), 353–362.
- Naesset, E., & Okland, T. (2002). Estimating tree height and tree crown properties using airborne scanning laser in a boreal nature reserve. *Remote Sensing of Environment*, 79(1), 105–115.
- Nelson, R., Valenti, M. A., Short, A., & Kelley, C. (2003). A multiple resource inventory of Delaware using airborne laser data. *Bioscience*, 53(10), 981–992.
- Popescu, S. C., Wynne, R. H., & Nelson, R. F. (2003). Measuring individual tree crown diameter with lidar and assessing its influence on estimating forest volume and biomass. *Canadian Journal of Remote Sensing*, 29(5), 564–577.
- Popescu, S. C., Wynne, R. H., & Scrivani, J. A. (2004). Fusion of small-footprint lidar and multispectral data to estimate plot-level volume and biomass in deciduous and pine forests in Virginia, U.S.A. *Forest Science*, 50(4), 551–565.
- Pyne, S. J., Andrews, P. L., & Laven, P. D. (1996). *Introduction to wildland fire*. New York: Wiley & Sons Press. 22–45 pp.
- Reeves, H. C. (1988). *Photo guide for appraising surface fuels in east Texas*. Center for Applied Studies at School of Forestry. Nacogdoches, Texas: Stephen F. Austin State University. 43–51 pp.
- Riano, D., Chuvieco, E., Salas, J., Palacios-Orueta, A., & Bastarrika, A. (2002). Generation of fuel type maps from Landsat TM images and ancillary data in Mediterranean ecosystem. *Canadian Journal of Forest Research*, 32, 1301–1315.
- Riano, D., Meier, E., Allgöwer, B., Chuvieco, E., & Ustin, S. L. (2003). Modeling airborne laser scanning data for the spatial generation of critical forest parameters in fire behavior modeling. *Remote Sensing of Environment*, 86(2), 177–186.
- Richards, J. A., & Jia, X. (2006). *Remote sensing digital image analysis: An introduction*. Springer. 207 pp.
- Roff, A., Goodwin, N., & Merton, R. (2005). *Assessing fuel loads using remote sensing*. School of biological, earth & environmental science technical report summary. NSW 2052 Australia: The university of New South Wales SYDNEY. 11–17 pp.
- Rollins, G. M., Keane, E. R., & Parsons, A. R. (2004). Mapping fuels and fire regimes using remote sensing, ecosystem simulation, and gradient modeling. *Ecological Applications*, 14(1), 75–95.
- Rome, W. H., Barry, P. J., Hanna, D. D., Floyd, M. L., & White, S. (2006). A wildfire hazard assessment and map for La Plata county, Colorado, USA. *Fire Ecology*, 2(1).

- Scott, J. H., & Reinhardt, E. D. (2001). Assessing crown fire potential by linking models of surface and crown fire behavior. *USDA, forest service research paper RMRS-RP-29*. Fort Collins, CO: Rocky Mountain Research Station. 9–21 pp.
- Smith, L. I. (2002). *A Tutorial on Principal Component Analysis*. Available at: http://csnet.otago.ac.nz/cosc453/student_tutorials/principal_components.pdf. Accessed March 25, 2006.
- Texas Forest Service (TFS). (2006). <http://texasforests.tamu.edu/shared/article.asp?DocumentID=1197>. Accessed April, 2006.
- Wagner, W., Eberhofer, C., & Summer, G. (2004). Robust filtering of airborne laser scanning data for vegetation analysis. *International Archives and Photogrammetry. Remote Sensing and Spatial Information Sciences*, 36(8), 56–61.