MAPPING SURFACE FUEL MODELS USING LIDAR and MULTISPECTRAL DATA FUSION FOR FIRE BEHAVIOR

Muge Mutlu* and Sorin C. Popescu

Spatial Science Laboratory, Department of Ecosystem Science and Management
Texas A&M University, 1500 Research Parkway, Suite B221, College Station, TX 77843, USA - mugemutlu@tamu.edu, s-popescu@tamu.edu

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ABSTRACT:

Improving the accuracy of mapping fuel models is important for fuel management decisions. The overall aim of this paper is to develop the use of LIDAR (LIght Detection and Ranging) remote sensing to accurately 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. We employ a unique approach to classify fuel models using a combination of LIDAR height bins and multispectral image data. According to Anderson (1982), a total of thirteen surface fuel models are identified for the United Stated, each varying in amount, size, and arrangement of the fuel model. 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. Different image processing approaches 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.

[1]1.INTRODUCTION

Fires have become intense and more frequent all over the world. Many forest fires occur each year and a huge amount of forest areas are lost in the United States. 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).
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).

* Corresponding author. Phone: +1 979 458-0742 Fax: + 1 979 862-2607. E-mail address: mugemutlu@tamu.edu (Muge Mutlu)

A total of thirteen surface fuel models are identified for the United Stated, each varying in amount, size, and arrangement of the fuel model (Anderson, 1982).

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 noncontextual algorithms (Jensen, 2005).

LIDAR 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. This technology is useful for obtaining accurate, high resolution measurements of surface elevations.

There is a limited number of studies in the literature that used airborne scanning laser (LIDAR) systems to estimate forest fuel parameters. Riano's (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.'s (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

Our study area is located in east Texas near Huntsville. Forest stands in study area are in various stages of development, including pine, pine-hardwood mixed stands, and hardwood stands (Mutlu et al., in press). The study area also includes open ground with fuels consisting of grasses and brushes. Figure 1 represents the QuickBird image of the study area.

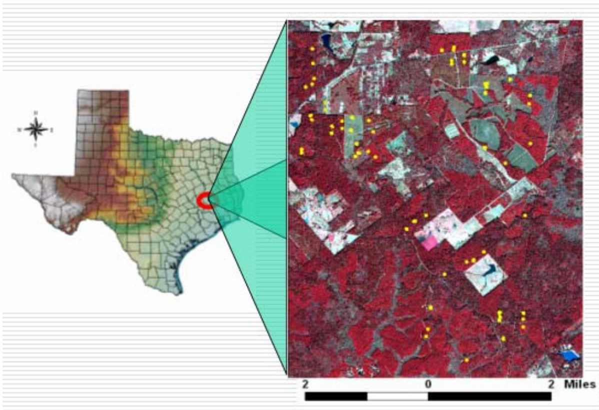


Figure 1. The location of our study area and false color composite of a QuickBird image

2.2 Data

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

2.3 LIDAR Data

LIDAR scanning data was provided by M7 Visual Intelligence Inc. in LAS format. LIDAR data were acquired over an area of 6,474.9 hectare (25 square miles) 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.

2.4 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.

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. 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. 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. Table 1 represents the description of each fuel model.

Table 1.Description of fuel models.

Fuel Model	Typical Fuel Complex
Grass and grass-dominated	
1	Short grass (foot)
2	Timber (grass-understory)
Chapparral and shrub fields	
4	Chapparal (6 feet)
5	Brush (2 feet)
7	Southern rough
Timber litter	
8	Closed timber litter
9	Hardwood litter

2.5 Processing Approach

The overall study steps to derive fuel maps are illustrated in Figure 2.

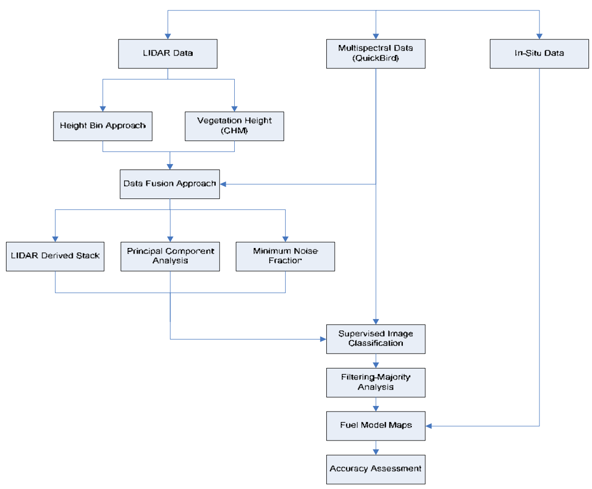


Figure 2: Overall study steps

2.6 Height Bins Approach

The height bin approach was used to generate a LIDAR-derived multiband dataset from scanning data, with each band corresponding to a height bin. The height bins approach makes use 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. The first four height bins are generated for 0.5m height intervals to afford a better characterization of vegetation that defines surface fuels. The upper bins are spaced at 3m and 5m, band 6 to 10. The last bin is generated from laser hits above 30m.

3. DATA FUSION APPROACH

In this study, three different data fusion approaches were used: LIDAR-multispectral stack, principal component analysis (PCA), and minimum noise fraction (MNF).

3.1 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 Figure 3, 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 meters), 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 2m vertical canopy space adjacent to the ground.

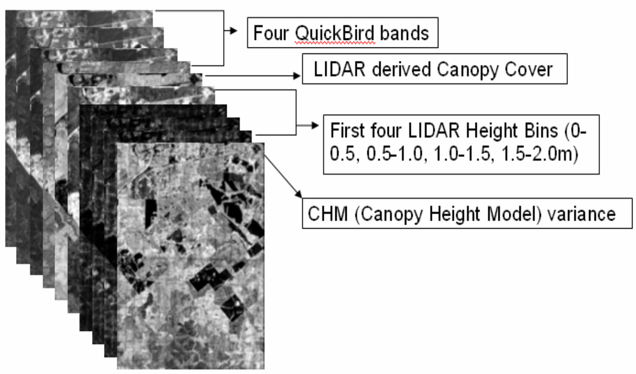


Figure 3: LIDAR-QuickBird stack image

3.2 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. The PCA transformation is based on the variance and covariance of the data set. Eigenvalues, variance, and eigenvector were extracted for each PC. The first five components that we used for image classification account for approximately 99 percent of the total variance.

3.3 Minimum Noise Fraction (MNF)

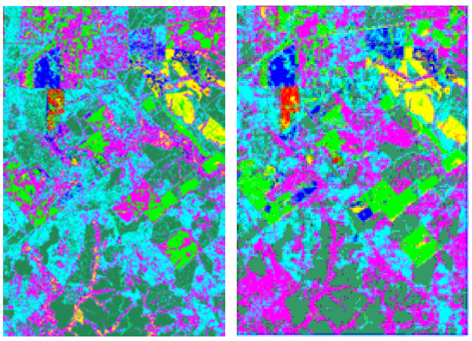
MNF was applied to the LIDAR-QuickBird stack image that has ten bands. MNF determines the dimensionality of image data, separates noise in the data, and reduces the computational requirements for processing (Boardman and Kruse, 1994). The MNF transform basically consists in two coupled Principal Components transformations (Green et al. 1988). Six of the ten MNF bands were stacked. Eigenvalues, percentage of variance, and cumulative variance were calculated for each MNF band. The first six MNF bands account for approximately 97 percent of the total variance. As such, we decided to use the first six components of the MNF band transformed image for our subsequent processing.

3.4 Image Processing

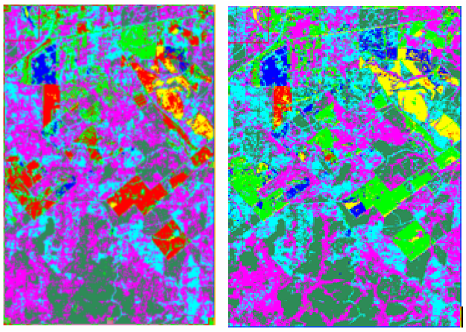
The first step in undertaking a supervised classification is to define the areas that will be used as training sites for each fuel model class. Seven initial classes were considered and classification accuracy was evaluated using confusion matrixes and K-hat statistics. The Region of interest (ROI) actually corresponds to our field plots. A total of twenty-three polygons were selected which results in a total of 1840 pixels for each of the QuickBird image, LIDAR-QuickBird stack image, principal component image, and minimum noise fraction image. 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.

4. 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 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. Figure 4(a) represents the result of multispectral QuickBird image classification; Figure 4(b) illustrates the result of the LIDAR-QuickBird stack image. Figure 4 (c) represents the results of the PC stack 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. Figure 4(d) illustrates the output of this classification process. Compared to the multispectral QuickBird image, LIDAR-QuickBird stack, and PC stack images accuracy, MNF provided the best result by having the highest accuracy.



(a) **(b)**



(c) **(d)**

Figure 4. (a) The classification result of multispectral QuickBird image, (b) the classification result of data fusion stack of LIDAR and multispectral imagery, (c) the classification result of PC stack image, and (d) the classification result of MNF-fused stack image.

5. 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. The 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. 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.

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