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ASSESSING FOREST FUEL LOADS and FIRE RISK ANALYSIS USING AIRBORNE AND SPACEBORNE LIDAR REMOTE SENSING DATA

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Crown fires can occur in any forest type throughout the world. The occurrence of crown fires has become increasingly frequent and severe in recent years. The overall aim of this study is to estimate the forest canopy fuel parameters including crown base height (CBH), canopy volume (CV), canopy cover (CC), and crown bulk density (CBD), and to investigate the potential of using lidar data in east Texas. The specific objectives are to: (1) develop a methodology for using airborne light detection and ranging (lidar) to estimate canopy fuel parameters and to simulate fire behavior using estimated forest canopy parameters as FARSITE inputs, and (2) investigate the use of spaceborne ICEsat /GLAS (Ice, Cloud, and Land Elevation Satellite/Geoscience Laser Altimeter System) lidar for estimating canopy fuel parameters. According to the results from our study, the CBD, CC, and CBH were successfully predicted using airborne lidar data with R^2 values of 0.748, 0.89, and 0.976, respectively. The study demonstrated that canopy fuel parameters can be successfully estimated using GLAS waveform data; an R^2 value of 0.84 was obtained. With these approaches, we are providing practical methods for quantifying these parameters and making them directly available to fire managers. The accuracy of these parameters is very important for realistic predictions of wildfire initiation and growth.

1. INTRODUCTION

The occurrence of wildland fires is an essential part of the natural cycle of the ecosystem (Johnson, 1992). Canopy fuel distribution is a critical factor for predicting fire behavior. The accurate prediction of the potential risk of a wildland fire can help reduce the seriousness of wildland fires.

Applications of various remote sensing systems and techniques to forest fire related research have been rapidly increasing in recent years. These techniques and systems can be used to decrease fire risk and reduce fire damage (Mutlu et al., 2008a; Andersen et al., 2005; Arroyo et al., 2008; Mutlu et al., 2008b). Airborne lidar remote sensing is an advanced technology for forestry applications and it has been applied to estimate surface fuel models and canopy fuel parameters (Mutlu et al., 2008a; Arroyo et al., 2008; Dubayah & Drake, 2000; Riano et al., 2003; Andersen et al., 2005; Hall et al., 2005; Morsdorf et al., 2004; Popescu & Zhao, 2008). The Geoscience Laser Altimeter System (GLAS) on the Ice, Cloud and land Elevation satellite (ICESat) is the first spaceborne lidar tool. This system was designed to measure and monitor ice sheet mass balance, cloud and aerosol heights, surface elevation changes, and vegetation characteristics (Zwally et al., 2002; Sun et al., 2008; Nelson et al., 2009; Simard et al., 2008). In recent years, ICESat/GLAS has been used in a number of forestry studies and has proven to have strong correlation with field-based aboveground biomass and canopy height measurements in extensive forests (Boudreau et al., 2008; Sun et al., 2008).

In this study, we aim is to estimate the forest canopy fuel parameters including crown base height (CBH), canopy volume (CV), canopy cover (CC), and crown bulk density (CBD), and to investigate the potential of using airborne and spaceborne lidar data in east Texas.

2. STUDY AREA

The study area is located in Huntsville, texas, USA. Vegetation comprises upland, bottomland hardwoods, coniferous, old growth pine stands, mixed stands, brushes, upland and bottomland hardwoods, and open ground with fuels consisting of grasses. Also, it is flat with average elevation is about 90 m. Figure 1 represents the multispectral QuickBird image of the study area.

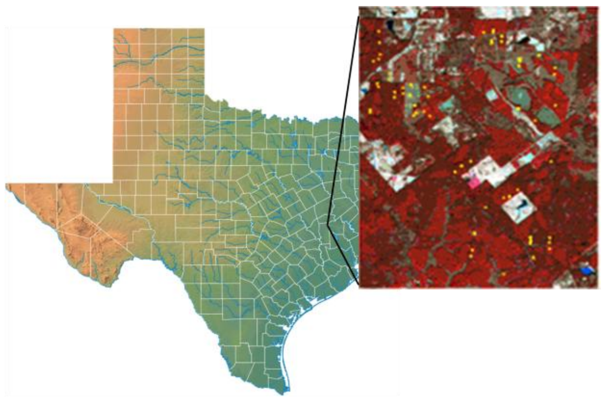


Figure 1. The location of our study area

3. MATERIALS AND METHODS

3.1 Data

Four types of data were used in this study: field data, a multispectral Quickbird image, airborne and spaceborne IceSat/GLAS lidar data.

3.1.1 Field Data

Field data were collected between May 2004 and July 2004. Ground reconnaissance was used to identify the potential plot locations in Huntsville, Texas. . Circular plots of two different sizes, a radius of 11.35 m (37.24 ft) covering a 404.7 m² (1/10th acre) and a smaller plot size of 40.468 m² (1/100-acre) with a radius of 3.59 m (11.78ft), were used in this study. Inside of each plot boundary, the following parameters were measured for each tree: diameter at breast height (dbh), total tree height, crown base height, and crown class.

3.1.2 Multispectral and Lidar Data

The multispectral Quickbird image used in this study (Fig. 4.1a) is a high resolution (2.5 x 2.5 m) satellite image in 2004. Airborne lidar scanning data over an area of 6,474.9 hectare (25 square miles) was obtained in leaf-off condition during March 2004. The lidar system (Leica-Geosystems ALS40) recorded two returns per laser pulse, first and last. The horizontal accuracy is 20-30 cm and vertical accuracy for the mission is 15 cm. The average point density is 2.58 laser points/m² and the maximum point density is 39.84 laser points/m². The average distance between laser points is 0.62 m for the entire point cloud. We were able to obtain GLAS data for our study area from February 2004 to October 2007 with GLAS sub-cycles from L2A to L3I from http://www.nsidc.org/data/icesat/order.html. Among all of the available GLAS data, we used the February 2004 GLAS data set obtained from GLAS L2B sub-cycle.

3.2 Processing Lidar Data

The height bins approach was used to generate lidar multiband data from airborne scanning lidar data (Popescu and Zhao, 2008). The height bins approach makes use of the entire lidar point cloud. Lidar bins were created by counting the occurrence of the number of lidar points within each volume unit and normalizing by the total number of points.
First, pixel size was set to 30 m resolution, which is larger than the actual plot size, to derive all lidar metrics to compensate for any GPS errors when locating ground plots. Similar to studies of Naesset and Bjerknes (2001), Erdody and Moskal (2010), and Andersen et al. (2005), eight lidar metrics were derived from the lidar point cloud including: 25^{th}, 50^{th} (median), 75^{th}, and 90^{th} of height percentiles of laser pulses, maximum height, mean height, coefficient of variation (cv), and canopy density (D), calculated as the number of all returns above 2.5 m divided by the total number of all returns at 30 m. In addition, logarithmic transformation was applied to our metrics. To estimate canopy fuel parameters from airborne lidar data, multiple predictive models were developed in this study.

Because no coincident field measurements are directly available over the footprints of GLAS shots, a two-phase approach were used in developing the regression models. First, a spatially-explicit map of CBH was derived from airborne lidar data. Then, the GLAS metrics were related to this lidar-derived canopy characteristic with multiple linear regression models. The canopy fuels were obtained from both the field data and the airborne lidar data. Figure 2 represents an example of waveform data collected by ICESat/GLAS.

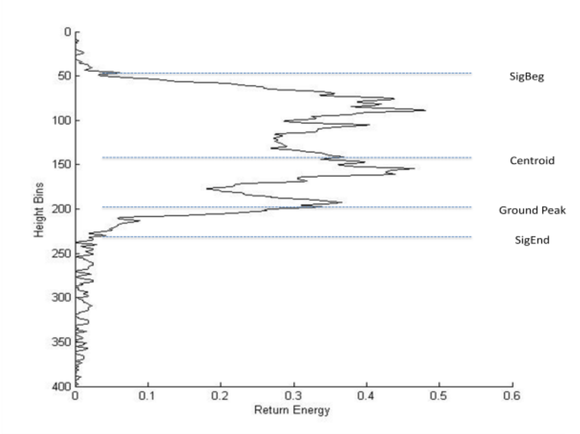


Figure 2. The GLAS example waveform over forest land.

Initially, a total of 48 GLAS waveforms were found and overlaid over the study area; however, only the 33 of the GLAS waveforms were used because no information was obtained from the rest of the footprints. A standalone peak finding algorithm developed by Neuenschwander et al. (2008) was used to process the GLAS waveform data. The GLA14 provides the latitude and longitude information. With the information obtained from GLA14, the last 392 records of each GLAS waveform (GLA01) were geolocated. After obtaining total waveform energy, the position of 0% (RH0), 25% (RH25), 50% (RH50-HOME (height of median energy)), 75% (RH75), 90% (RH90), and 100% (RH100) percentile heights were computed starting from the signal ending by computing a cumulative distribution function of GLAS waveform energy. A total of ten GLAS metrics were derived and used in our regression analysis to estimate canopy fuels. Figure 3 the overall view of the ICESat/GLAS footprints over lidar-derived CBH map of the study area.

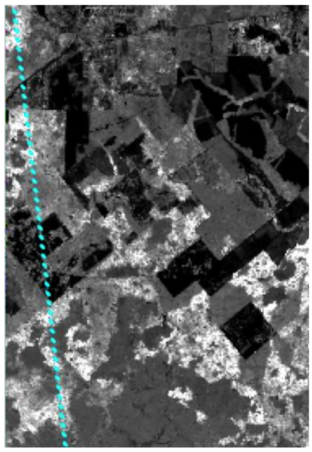
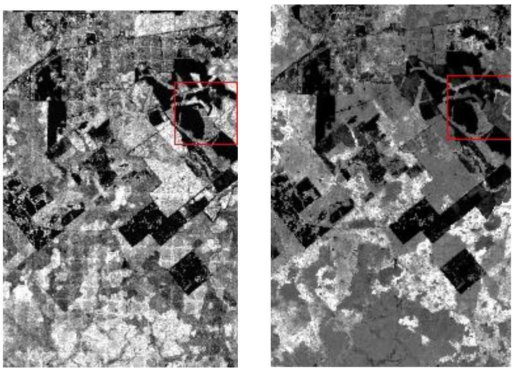


Figure 3. The ICESat/GLAS footprints overlaid on the airborne lidar-derived wall-to-wall CBH map of our study area.

4. RESULTS

As a result, CBD used as field data always provided better models in metrics set. To illustrate the goodness-of-fit of the data and select the best fitted model for predicting CBD, all regression models were plotted. For CBH, among all the models, the best-fitted equation was obtained from metrics-set-1 with R^2 value of 0.976 and adjusted R^2 value of 0.973. For CBD, the best fitted equation was obtained from metrics-set-3 with R^2 value of 0.748 and adjusted R^2 value of 0.726. The highest R^2 and adjusted R^2 values were used to identify the best fitted model for CBD and CBH, not the lowest log-transformed RMSE. The CBD (Figure 4.a) and CBH (Figure 4.b) maps were generated in ENVI using Band Math function based on the selected regression models. According to the results from our study, the CBD, CC, and CBH were successfully predicted using airborne lidar data with R^2 values of 0.748, 0.89, and 0.976, respectively. According to regression analysis result, GLAS height metrics and lidar-derived CBH were highly correlated in this study.



(a) (b)

Figure 4. (a) The CBD map; (b) The CBH map of our study area.

Canopy cover estimated from GLAS data without any CBH threshold yielded a log trend when compared to the airborne LiDAR. Canopy cover estimated as the ratio of canopy energy to the total energy of the waveform without applying any CBH threshold, showed a log trend with 57.6% of the variance explained. Strong agreement was found between GLAS CC estimates and airborne LiDAR CC estimates when the latter was derived from intensity data. The use of intensity data to generate CC from airborne LiDAR showed a good agreement (around 7%) with GLAS data. When the range capability of airborne LiDAR data is used, only the presence/absence of a reflection surface is accounted for but not the amount of energy returned to the sensor.

Figure 5. Canopy Cover map derived from lidar data

Using airborne lidar data, we were able to derive the two required CBH, CC, and CBD canopy fuel parameters to simulate crown fires in FARSITE. Surface fuel model, CBD, CC, and CBH maps are very difficult to derive and many fire managers do not have these inputs to run FARSITE. We developed all the spatial data layers for our study area. To simulate crown fire over the study area, a plot was selected and plot center location was used as an ignition point in FARSITE simulations. Inside of this plot boundary, we have a total of 57 trees with an average total tree height of 52.1 m. The duration of this simulation was set to 48 hours beginning at 8:00 AM and ending at 8:00 AM two days later. Weather and wind data, gathered on March 1, 2004, were used for all runs of FARSITE because dryer periods occur during September – October and February – March in the study area. Figure 6 represents the snapshot of FARSITE run. The result of FARSITE simulation shows that the estimated burned area was 463 ha (1144.57 ac) and the perimeter was 12.6 km (7.8 miles) for the selected plot (Liv#21). These results are important because a significant risk to life and property exists wherever forest stands are prone to crown fire.

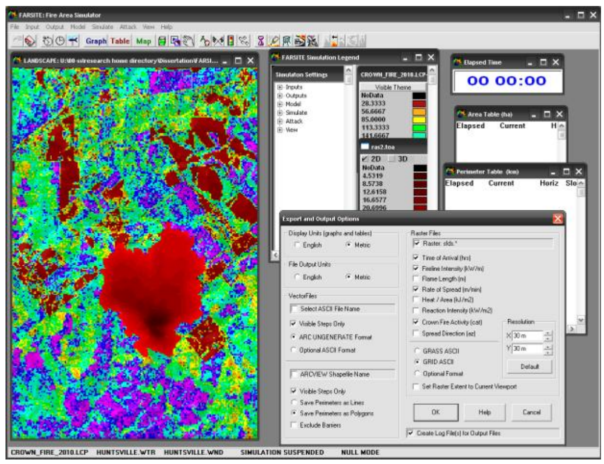


Figure 6. A snapshot from crown fire simulation software, FARSITE.

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