USING LIDAR-DERIVED FUEL MAPS WITH FARSITE FOR FIRE BEHAVOIR MODELING

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ABSTRACT

Fires have become intense and more frequent in the United States. Fuel distribution is very important for predicting fire behavior. The overall aim of this project is to model fire behavior using FARSITE and investigate differences in modeling outputs using fuel model maps, which differ in accuracy, in east Texas. This software requires as input spatial data themes such as elevation, slope, aspect, surface fuel model, and canopy cover along with separate weather and wind data. Seven fuel models, including grass, brush and timber models, are identified in the study area. To perform modeling sensitivity analysis, two different fuel model maps were used, one obtained by classifying a QuickBird image and the other obtained by classifying a LIDAR and QuickBird fused data set. Our previous investigations showed that LIDAR improves the accuracy of fuel mapping by at least 10%. According to our new results, LIDAR derived data also provides more detailed information about characteristics of fire. This study will show the importance of using accurate maps of fuel models derived using new LIDAR remote sensing techniques.

INTRODUCTION

Forest fire is a critical issue all over the world. Forest fires destroy many houses and natural resources such as plant and animal life each year. Fire behavior is very sensitive to changes in weather and wind conditions, and topography. Recent advances in computer software technology have allowed development of several spatially explicit fire behavior simulation models, which predict the spread and intensity of fire (Andrews, 1989). FARSITE is a two-dimensional deterministic model for simulating the spatial and temporal spread and behavior of fires under conditions of heterogeneous terrain, fuels, and weather (Finney, 1998). FARSITE is based on spatial data, and thus it is a powerful tool for the fire manager.

The accuracy of the input data layers are very important for realistic predictions of fire growth (Keane et al., 1998, Finney 1998). The fuel model map is the key input for the simulation model. Satellite technology can assist in providing data for the FARSITE software (Chuvieco, 1997). The use of airborne LIDAR (Light Detection and Ranging) allows scientists to measure the three-dimensional distribution of forests, and it 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 the object sensed (Wagner et al., 2004).

Multispectral image classification is an important technique in remote sensing and image analysis. Mutlu et al. (in review) specifically mapped fuels for FARSITE use, and their results are used in this paper. The authors applied supervised image classification, to determine which classifier is more efficient and useful for two different fuel model maps that they created. These fuel model maps include a total of seven fuel models. The first fuel model map was obtained by classifying only a high-resolution QuickBird satellite image and the second one was obtained by classifying a LIDAR and QuickBird fused data set. The investigations of Mutlu et al. (in review) show that LIDAR improves the accuracy of fuel mapping by at least 13%. The other inputs will stay the same for each run of FARSITE.

The main objectives of this paper are to model fire behavior using FARSITE and investigate differences in modeling outputs using fuel model maps, which differ in accuracy, in east Texas. This study will show the importance of using accurate maps of fuel models derived using new LIDAR remote sensing techniques.

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. The study area includes open ground with fuels consisting of grasses and brushes. Figure 1 represents the QuickBird image of the study area.

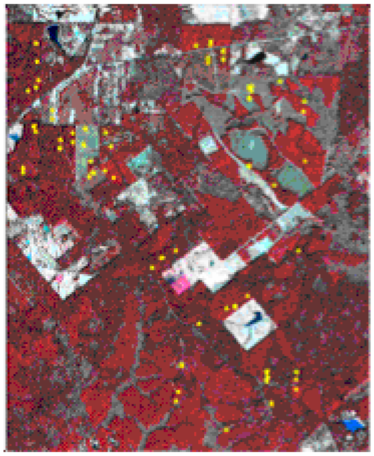


Figure 1. The false color composite of a QuickBird image of our study area and, with field plot locations.

METHODS

Two different fuel model maps obtained from Mutlu et al (in review) were used to see the differences in fire growth with fuel model maps of different accuracies (see Figure 2 (a) and (b)).

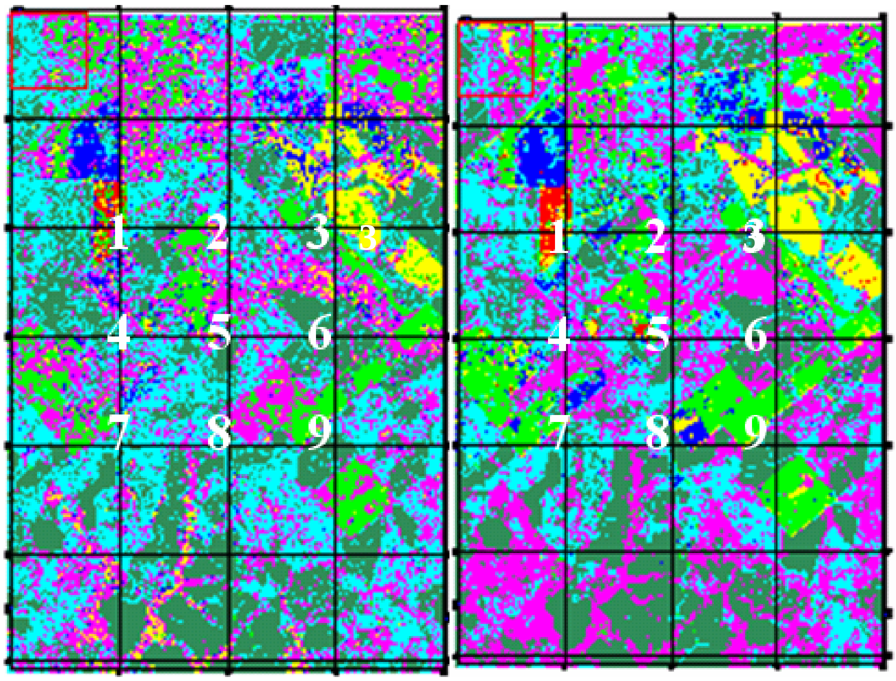
Data

FARSITE software requires eight data layers including Digital Elevation Model (DEM), slope, aspect, canopy cover, fuel models map, weather, wind, and fuel moisture for surface fire simulations (Finney, 1995). Two different input data sets were used in this study to generate real-time fire simulation outputs.

Dataset with QuickBird-derived Fuel Map

The second map, shown in Figure 2(a), was derived from QuickBird data at 2.5 m resolution. Based on the report from Mutlu et al. (in review), a maximum likelihood image classification was used to classify the multispectral image. This fuel model map also includes seven fuel models.

The DEM was downloaded from the National Fire and Aviation Managament Web Applications (http://www.fs.fed.us/fire/planning/nist/wims_web_userguide.htm) at 30 meter resolutions, and then converted to 2.5 meter resolution. The slope and aspect data were derived from the DEM in ENVI. Weather and wind data were also downloaded from the National Fire and Aviation Managament Web Applications for both datasets. Canopy cover and fuel moister were developed based on field data.



(a) (b)

Figure 2. (a) The fuel map obtained by classifying a LIDAR and QuickBird fused data set, (b) the fuel model map obtained by classifying a QuickBird image [Gridlines and fire ignition points are included].

Dataset with LIDAR_derived Fuel Map

We developed all the spatial data layers, which are required by FARSITE. The first fuel model map at 2.5 m resolution was derived from LIDAR and is shown in Figure 2(b). Based on Mutlu et al (in review), a LIDAR-QuickBird stack image of ten bands was created by stacking the four bands of the QuickBird image with four LIDAR height bins, one band from the canopy cover model, and one band from the canopy cover variance. In addition, the height bin approach was used to generate LIDAR multiband data from scanning data. LIDAR bins were created by counting the occurrence of LIDAR points within each volume unit and normalizing by the total number of points (Popescu and Zhao, in review). Figure 3 shows the LIDAR-QuickBird stack image. Canopy cover, the horizontal percentage of area covered by tree crowns at the stand level, was found using methods developed by Griffin and Popescu (in review). DEM was also obtained from LIDAR. By using ENVI software, slope and aspect were derived from the DEM.

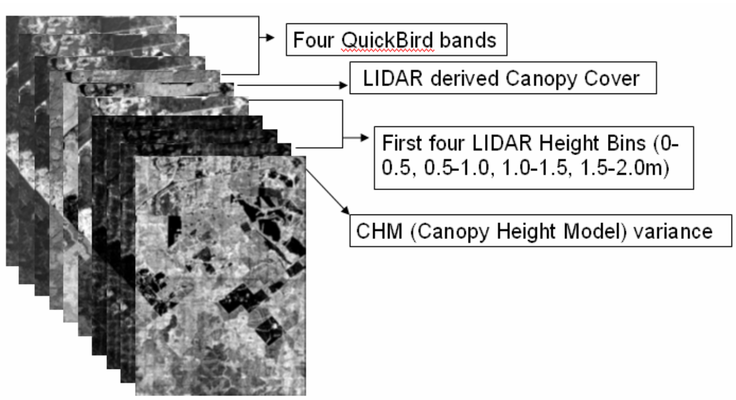


Figure 3. The LIDAR-QuickBird stack image.

FIRE SIMULATIONS

Both fuel model maps were divided into 24 grids, four columns and six rows. Each grid space is 558 pixels. We chose nine center-points from nine grids on each map. These grids are located in the middle of the study areas (see Figure 2(a) and (b)). FARSITE was run eighteen times, nine times on the dataset with the LIDAR-derived fuel model map and nine times on the dataset with the QuickBird-derived fuel map. Figure 4 shows a screenshot from the FARSITE simulation. The duration of each simulation was 72 hours beginning at 8:00 AM and ending at 8:00 AM three days later. The most extreme weather and wind data, which occurred on January 14, were used for all runs of FARSITE.

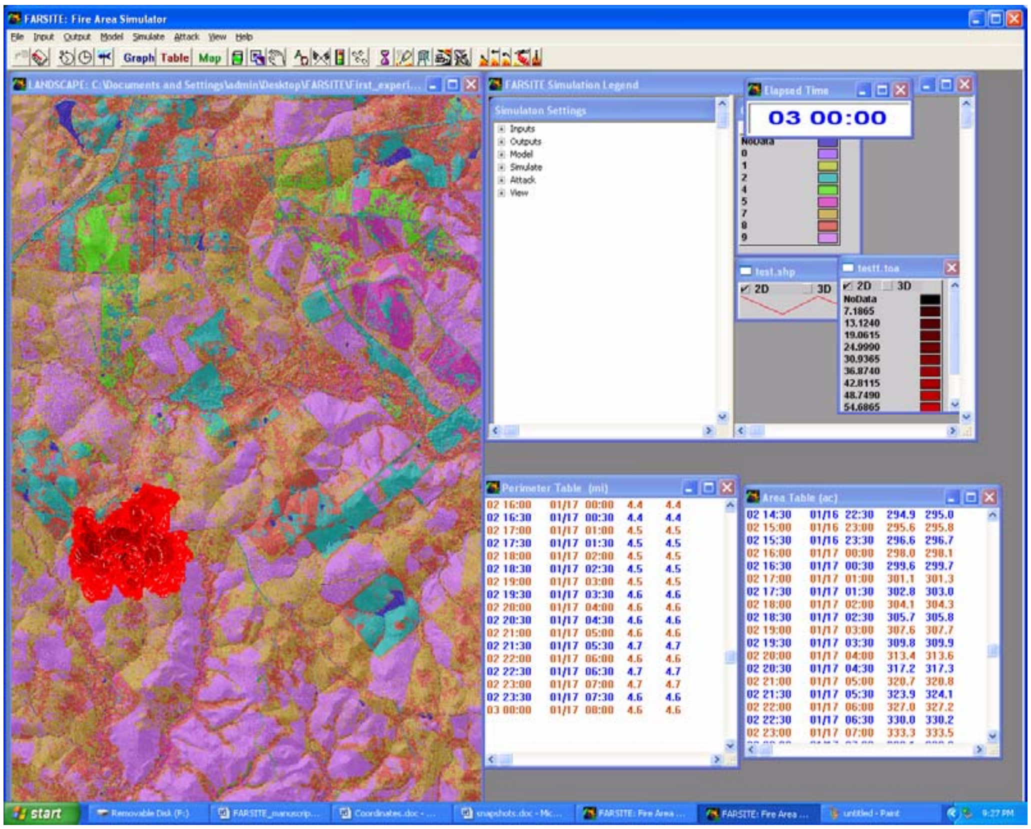
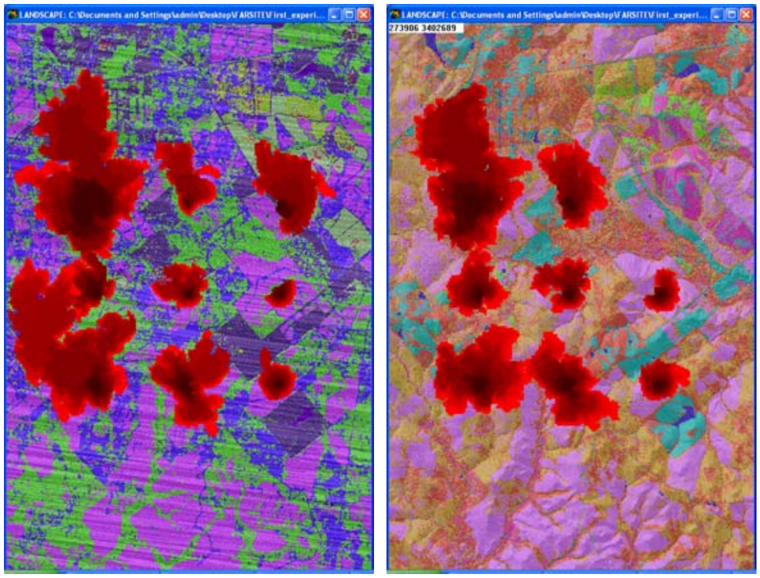


Figure 4. Screenshot from the fire simulation.

RESULTS AND DISCUSSION

Figure 5(a) and (b) represent the fire growth outputs for the LIDAR-derived fuel model map and the QuickBird-derived fuel model map. The comparisons of the burned area results per half an hour are illustrated in Figure 6. Figure 7 demonstrates the comparison of the fire perimeters between the two maps per half an hour for 72 hours. Based upon the fire simulation results, fuel model map derived from LIDAR shows larger fire growth areas than the other fuel model map derived from QuickBird imagery.



(a) (b)

Figure 5. (a) The results of fire simulations for the LIDAR-QuickBird fuel map, (b) the results of fire simulations for the QuickBird fuel model map.

The estimated total fire growth areas from LIDAR-derived fuel model map and QuickBird derived fuel model map were approximately 2243 ac and 1862 ac, respectively. Apparently, there is a significant difference between the two outputs. Especially, there are important differences on 3rd and 7th runs. On the third run, while 230 ac were burned on LIDAR-derived fuel model map, almost 0 ac was burned on QuickBird-derived fuel model map. On the seventh run, the burned area on the LIDAR-derived fuel model map is almost two times larger than the burned area from the QuickBird-derived fuel model map. The same correlation can be seen in Figure 7 for fire perimeters for both models.

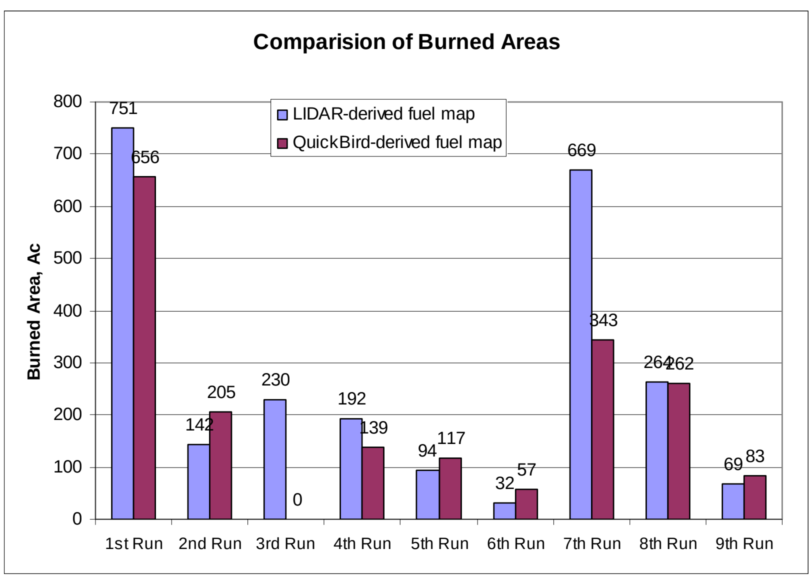


Figure 6. Comparison of burned areas for both fuel model maps.

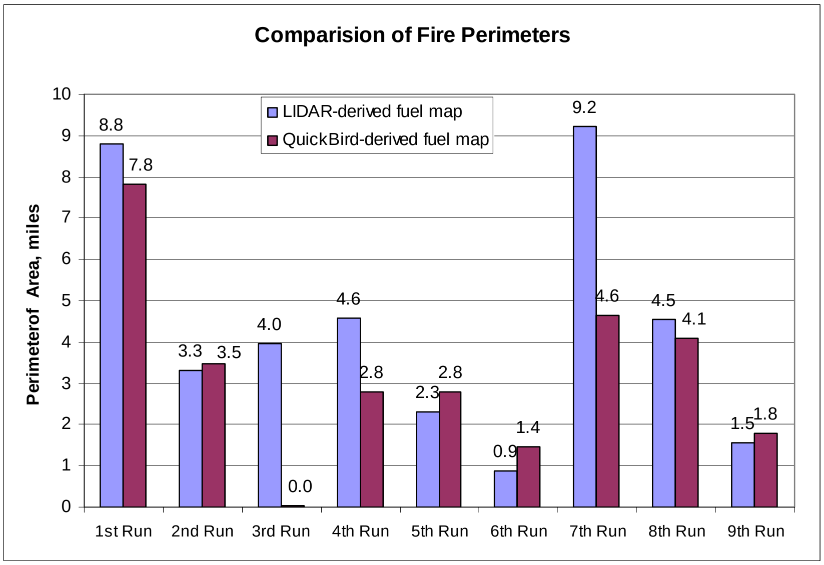


Figure 7. Comparison of fire perimeter results for both fuel model maps.

CONCLUSION

Results from this study indicate the influence of a more accurate fuel map on modeling fire behavior and assessing fire risk. According to results, LIDAR derived data provides more detailed information about characteristics of fire. LIDAR derived products were able to assess fuel models with high accuracy and it provided different fire perimeters and fire growth area. Using two different datasets, one derived from LIDAR and the other one derived from QuickBird imagery and different data sources, provided significantly different outputs. The differences could be attributed to different fuel model map, canopy cover, DEM, slope, and aspect. This information will be more useful if it is used by fire management authorities. This process will provide managers with a strategic view of the state to improve public safety.

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