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Developing custom fire behavior fuel models from ecologically complex fuel structures for upper Atlantic Coastal Plain forests

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ABSTRACT

Currently geospatial fire behavior analyses are performed with an array of fire behavior modeling systems such as FARSITE, FlamMap, and the Large Fire Simulation System. These systems currently require standard or customized surface fire behavior fuel models as inputs that are often assigned through remote sensing information. The ability to handle hundreds or thousands of measured surface fuelbeds representing the fine scale variation in fire behavior on the landscape is constrained in terms of creating compatible custom fire behavior fuel models. In this study, we demonstrate an objective method for taking ecologically complex fuelbeds from inventory observations and converting those into a set of custom fuel models that can be mapped to the original landscape. We use an original set of 629 fuel inventory plots measured on an 80,000 ha contiguous landscape in the upper Atlantic Coastal Plain of the southeastern United States. From models linking stand conditions to component fuel loads, we impute fuelbeds for over 6000 stands. These imputed fuelbeds were then converted to fire behavior parameters under extreme fuel moisture and wind conditions (97th percentile) using the fuel characteristic classification system (FCCS) to estimate surface fire rate of spread, surface fire flame length, shrub layer reaction intensity (heat load), non-woody layer reaction intensity, woody layer reaction intensity, and litter–lichen–moss layer reaction intensity. We performed hierarchical cluster analysis of the stands based on the values of the fire behavior parameters. The resulting 7 clusters were the basis for the development of 7 custom fire behavior fuel models from the cluster centroids that were calibrated against the FCCS point data for wind and fuel moisture. The latter process resulted in calibration against flame length as it was difficult to obtain a simultaneous calibration against both rate of spread and flame length. The clusters based on FCCS fire behavior parameters represent reasonably identifiable stand conditions, being: (1) pine dominated stands with more litter and down woody debris components than other stands, (2) hardwood and pine stands with no shrubs, (3) hardwood dominated stands with low shrub and high non-woody biomass and high down woody debris, (4) stands with high grass and forb (i.e., non-woody) biomass as well as substantial shrub biomass, (5) stands with both high shrub and litter biomass, (6) pine-mixed hardwood stands with moderate litter biomass and low shrub biomass, and (7) baldcypress-tupelo stands. Models representing these stand clusters generated flame lengths from 0.6 to 2.3 m using a 30 km h^{-1} wind speed and fireline intensities of 100–1500 kW m^{-1} that are typical within the range of experience on this landscape. The fuel models ranked 1 < 2 < 7 < 5 < 4 < 3 < 6 in terms of both flame length and fireline intensity. The method allows for ecologically complex data to be utilized in order to create a landscape representative of measured fuel conditions and to create models that interface with geospatial fire models.

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1. Introduction

Fire management requires an understanding of the spatial distribution of fuels and fire behavior parameters over large landscapes to assess risk, plan treatments and monitor effectiveness of those treatments. Various geospatial models, such as FARSITE, FlamMap, and the Large Fire Simulation System (e.g. Finney, 2004), are available to simulate fire behavior over large landscapes if standard or customized surface fire behavior fuel models (FBFMs) are available and can be linked to canopy structure (Arroyo et al., 2008; Scott and Burgan, 2005; Fernandes et al., 2006; Hollingsworth et al., 2012). However, ecologically variable and complex surface fuels are a barrier to modeling fire behavior at

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the landscape scale and monitoring the effectiveness of treatments. The problem of validating treatment effectiveness and the threshold for retreatment will become more important in the future as limited resources are available for risk reduction (Fernandes and Botelho, 2003).

Even if the surface fuels themselves change little over time, it can be challenging to account for the spatial variation in surface fuels and to predict patterns. Progress has been made over the last several decades in using statistical modeling to predict and explain the distribution of surface fuels with varying degrees of success. Several studies have successfully used hierarchical approaches involving cluster analysis and regression trees to model fuels with reasonable precision and limited bias over large areas (Keane et al., 2001; Rollins et al., 2004; Reich et al., 2004; Poulos et al., 2007). More recently Pierce et al. (2009) evaluated several methods including gradient nearest neighbor, linear models, regression trees and several geostatistical methods to map fuels in western Washington, Oregon and California. The gradient nearest neighbor approach worked well at very large scales, but not at small scales, and other models faired poorer. The common element in these previous studies was the presence of strong geospatial gradients, such as elevation, aspect, etc., within relatively natural systems. Therefore, natural environmental processes likely dominated spatial patterns.

Although it is possible to predict the spatial distribution of surface fuels themselves, it is far more difficult to reliably establish the spatial distribution of FBFMs because of the complex interactions between fuel components that generate fire behavior (see Cruz and Fernandes, 2008). The result has been that models are assigned to locations on the landscape from remote sensing imagery associated with limited field data and verification (Andreu and Hermansen-Baez, 2008; Arroyo et al., 2008; Rollins, 2009). These models are believed adequate for coarse scale assessment. As Reich et al. (2004) stated, “Comprehensive fuel models take considerable sampling effort, and are largely impossible for developing spatial models based on ground surveys.” Despite this daunting prediction, efforts are being made to link field inventory data directly to FBFMs (Fernandes et al., 2006).

Large complex inventory data sets are difficult to translate into fuel models. Simple replacement of fuel loading values in standard FBFMs is usually inappropriate. In order to use real sample data to improve fire behavior modeling on the landscape, a method to reduce the ecologically complex fuel components to similar FBFMs is required. The key to this dilemma is to first convert surface fuel components to fire behavior parameters, such as with the fuel characteristic classification system (FCCS) (Ottmar et al., 2007; Sandberg et al., 2007), and then to apply statistical methods to group and predict the spatial distribution. We demonstrate an objective statistical approach in which complex fuel conditions generated through ecological factors and management activities can be simplified to generate a limited set of custom FBFMs to characterize large landscapes. The latter approach allows for the application of landscape fire behavior modeling tools and the use of periodic survey, monitoring or inventory information to update and improve modeling where vegetation conditions are dynamic. This approach is applied to an 80,000 ha managed forest landscape in the upper Atlantic Coastal Plain of South Carolina, USA with a long history of man-made disturbances that often override natural processes that once dominated the landscape.

1.1. Objective

The overall objective of our study was to develop a method to convert a large number of ecologically complex surface fuelbeds into a set of custom fuel models with fire behavior parameters that can be mapped to the original landscape (Hollingsworth et al., 2012). The goal in the study is to achieve a practical compromise in order to create a reasonable number of fire behavior fuel models that can be used with fire spatial models, but also models that represent the landscape. The practical compromise will result in the loss of information as it collapses the spatial variability into groups or populations with distinct fire behavior parameters. However, this compromise facilitates the use of inventory or monitoring data within the current demands of FlamMap and FARSITE. The underlying principles to this method are: (1) imputing fuel component loads from plot measurements to ecologically similar units (Parresol et al., 2012), (2) performing cluster analysis on the FCCS fire parameters, and not the fuels themselves, (3) creating custom fire behavior fuel models based on the centroid fuelbeds calibrated to the FCCS point estimates for wind and fuel moisture, and (4) mapping the custom models back to the original landscape based upon the clustering of the ecological units.

2. Materials and methods

2.1. Study area

The landscape under study was The United States Department of Energy Savannah River Site (SRS), an 80,000 ha National Environmental Research Park, near Aiken, South Carolina (Kilgo and Blake, 2005). The SRS is located on the Upper Coastal Plain and Sandhills physiographic provinces in South Carolina, USA. The SRS today contains approximately 74,000 ha of forested landscape divided into over 6000 stands. When the SRS was established in 1951, approximately 33,000 ha were in old-fields and the balance consisted of cutover forest land with low stocking (Kilgo and Blake, 2005). The old fields and cutover forests were planted with loblolly pine (*Pinus taeda* L.), longleaf pine (*Pinus palustris* Mill.) and slash pine (*Pinus elliottii* Engelm. var. *elliottii*; planted outside of its natural range).

2.2. Fuel measurements and stand values

Fuel values were measured on 629 inventory plots systematically placed across the landscape. Surface fuels constitute the biomass of: duff and litter; 1-h timelag, 10-h timelag, 100-h timelag, and 1000-h timelag down woody debris; shrubs and small trees; vines, forbs, grasses and grass-like plants. For details on the fuels inventory see Parresol et al. (2012). From the inventory data, values for all fuel strata were imputed for each of the 6329 stands on the landscape from the linkage variables forest type, age, site index, basal area and recent fire history. For details on the stochastic based imputation process see Parresol et al. (2012).

2.3. Processing of fuel values to obtain surface fire behavior

The fuel characteristic classification system (Ottmar et al., 2007; Sandberg et al., 2007) is a tool that uses inventoried fuelbed inputs to predict crown and surface fire behavior (Andreu et al., 2012; Hollingsworth et al., 2012). We processed the stand fuel values through the FCCS under 97th-percentile fire weather conditions and output the following fire behavior parameters: (1) surface fire rate of spread in m min^{-1} (ROS), (2) surface fire flame length in m (FL), (3) shrub layer reaction intensity (heat load) in kJ m^{-2} min^{-1} (RI_Shrub), (4) non-woody layer reaction intensity in kJ m^{-2} min^{-1} (RI_Nonwoody), (5) woody layer reaction intensity in kJ m^{-2} min^{-1} (RI_Woody), and (6) litter–lichen–moss layer reaction intensity in kJ m^{-2} min^{-1} (RI_LLM).