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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).

2.4. Cluster analysis

2.4.1. Data considerations

We examined the data for outliers. Outliers affect distance measures in clustering and should be removed (Everitt, 1980). It is necessary to consider scaling or transforming the variables used in cluster analysis because variables with large variances tend to have a larger effect on the resulting clusters than variables with small variances. Possibilities are standardizing the data, doing a linear transformation (to transform the data into a within-cluster covariance matrix) or rescaling the RI variables. The idea behind rescaling the RI variables is to bring them down to a dimensionality similar to the remaining variables. Considering the units of measure for ROS (m min^{-1}) and the RIs ($\text{kJ m}^{-2}\text{ min}^{-1}$), taking the cubic root of the RIs should reduced their dimensionality to that of ROS. Finally, one should check for collinearity among the variables because highly correlated variables tend to obscure clusters (Everitt, 1980).

2.4.2. Clustering techniques

The clustering was done with the hierarchical CLUSTER procedure in SAS software (SAS, 2009) using two methods: (1) Ward's minimum-variance method, and (2) two-stage density linkage with $K = k$ nearest neighbors (nonparametric probability density estimation). Density linkage applies no constraints to the shapes of the clusters and, unlike most other hierarchical clustering methods, is capable of recovering clusters with elongated or irregular shapes (SAS, 2009).

There are no completely satisfactory methods for determining the number of population clusters for any type of cluster analysis (Everitt, 1979; Bock, 1985; Hartigan, 1985). Two popular methods are the pseudo F statistic, and the pseudo T^2 statistic. Normally one looks for consensus among the statistics, that is, local peaks of the pseudo F statistic combined with a small value of the pseudo T^2 statistic and a larger pseudo T^2 for the next cluster fusion. For two-stage density linkage the number of clusters is a function of the smoothing parameter K. The number of clusters tends to decrease as the smoothing parameter increases, but the relationship is not strictly monotonic. One useful descriptive approach to the number-of-clusters problem is provided by Wong and Schaack (1982). Density linkage is applied with varying values of K and each value of K yields an estimate of the number of modal clusters. If the estimated number of modal clusters is constant for a range of K values, there is evidence of that many modes in the population. A plot of the estimated number of clusters against K will show the trend and be informative for choosing the number of clusters. As a means of assessing the accuracy of a cluster analysis, that is, the separation into clusters, we ran a discriminant analysis.

2.5. Fire behavior fuel models

If p points are embedded in an n-dimensional space, then the c clusters established by the clustering algorithm can be summarized by their respective centroids in that space. The centroid is the average of all the p points in the cluster, that is, its coordinates are the arithmetic mean for each dimension separately over all the points in the cluster. The Euclidean distance or Euclidean metric is the "ordinary" distance between two points. The Euclidean distance between points $\mathbf{x} = (x_1, x_2, \ldots, x_n)$ and $\mathbf{y} = (y_1, y_2, \ldots, y_n)$, in Euclidean n-space, is defined as:

$$d(\mathbf{x},\mathbf{y}) = \|\mathbf{x}-\mathbf{y}\| = \sqrt{(x_1-y_1)^2+(x_2-y_2)^2+\cdots+(x_n-y_n)^2} = \sqrt{\sum_{i=1}^{n}(x_i-y_i)^2}. \quad (1)$$

For each point (i.e., stand) in each cluster we computed the Euclidean distance between the cluster centroid point $\mathbf{x}$ and the stand point $\mathbf{y}$.

Stands with the closest Euclidean distance to the centroid fuel values are used to build the custom fire behavior fuel models that are calibrated to critical FCCS parameters. The development is a three step process. The first step is to create initial fuel models from the Rothermel (1972) spread equation. The 12 parameters are initialized from stands data close to cluster centroid values and ancillary data on surface–area-to-volume ratios (SAV), moisture of extinction, heat content, etc. The second step is to obtain fire behavior calibration weather and fuel moisture information. The Savannah River Remote Automated Weather Station (RAWS) data from February 20, 1993 to April 20, 2009 were analyzed to develop an array of fuel moisture and wind conditions for calibration. We developed three scenarios of dead and live fuel moisture representing moderate, high, and extreme conditions (Table 1). Each of these was combined with three mid-flame wind speeds, 1.6, 4.8, and 9.7 km h^{-1}, to develop nine calibration points. The final step is using the nine calibration data points to adjust the initial fuel model parameters so that fuel-model predicted fire behavior matches FCCS-predicted fire behavior.

3. Results

3.1. Cluster analysis

Through trial and error with many cluster runs, we determined that data standardization and linear transformation were not as effective as rescaling the RI variables for determining and delineating clusters. What follows are the results based on using the rescaled reaction intensity variables. First we graphically examined variable values looking for outliers. Finding none, we computed correlations on the six variables to look for collinearity problems. A strong correlation is defined as $r > 0.8$. We see in Table 2 that FL is strongly correlated with ROS ($r = 0.893$) and RI_Shrub$^{1/3}$ ($r = 0.792$). Based on having two substantive correlations on FL, we excluded it from the cluster analysis.

Both clustering approaches resulted in 7 clusters. For Ward's method, the pseudo F statistic had a local peak at 4 clusters and the pseudo T^2 statistic pointed to 4, 7, and 11 clusters as possibilities (Fig. 1). The R^2 value for 7 clusters is 0.73. For the density method, Fig. 1 displays the number of clusters versus values of K and indicates 7 clusters are optimal. The R^2 for 7 clusters with the density method is 0.65. We examined cluster membership from both methods and looked at graphs of the clusters in canonical space. The clusters were more readily interpretable (Table 3) and exhibited less overlap spatially (i.e., the clusters were more distinct) (Fig. 2) with Ward's method. Also, the clustering using Ward's method resulted in a higher R^2 value, so we chose to work with the clusters from Ward's method to build the fire behavior fuel models. In Table 4 we give the output from a discriminant analysis of the clusters using the FCCS fire behavior parameters (excluding FL) as independent variables in the linear discriminant function.

The pine-dominated cluster 1 with its high litter and down woody debris biomass (relative to the other clusters) contains 2815 of the 6329 stands or 44% of the stands. The hardwood and pine stands with no shrub layer make up cluster 2 and account for 534 or 8.5% of the stands. The hardwood-dominated cluster 3 with its relatively high non-woody and woody biomass and low shrub biomass contains 1578 or 25% of the stands. The pine and hardwood stands with relatively high grass and forb biomass and containing a substantial shrub layer and down woody debris make up cluster 4 and account for 636 or 10% of the stands on the SRS. Cluster 5 consists of a combination of pine and hardwood stands,

Table 1
Dead and live fuel moisture scenarios (values in percent).

Fire danger	1 h timelag fuel	10-h timelag fuel	100-h timelag fuel	Live herbaceous	Live woody
Moderate	7	10	15	80	140
High	6	9	14	70	130
Extreme	5	7	12	60	110

Table 2
Pearson correlation matrix on the six FCCS variables. Entries are correlation coefficients, $n = 6329$. All correlations are significant ($P < 0.0001$) except FL versus RI_Woody$^{1/3}$ ($P = 0.34$).

	ROS	FL	RI_Shrub$^{1/3}$	RI_Nonwoody$^{1/3}$	RI_Woody$^{1/3}$	RI_LLM$^{1/3}$
ROS	1.0	0.8930	0.5319	−0.2588	−0.2834	0.1462
FL	0.8930	1.0	0.7918	−0.2369	0.0119	0.2961
RI_Shrub$^{1/3}$	0.5319	0.7918	1.0	−0.1125	0.2648	0.1695
RI_Nonwoody$^{1/3}$	−0.2588	−0.2369	−0.1125	1.0	0.2871	−0.2471
RI_Woody$^{1/3}$	−0.2834	0.0119	0.2648	0.2871	1.0	0.1837
RI_LLM$^{1/3}$	0.1462	0.2961	0.1695	−0.2471	0.1837	1.0

ROS is rate of spread in m min^{-1}. FL is flame length in m. The prefix RI means reaction intensity in kJ m^{-2} min^{-1}. LLM is the litter–lichen–moss layer. The RI variables have been rescaled by taking the cubic root.

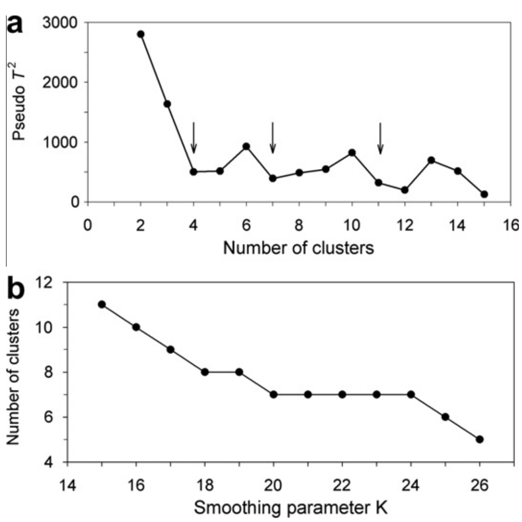

Fig. 1. Graphs for determining the number of population clusters. (a) For Ward's clustering method, the pseudo T^2 statistic indicates 4, 7, or 11 clusters are viable choices. (b) For the density method the number of clusters versus values of K indicates 7 clusters are optimal.

and when compared to the other clusters, has considerable shrub and litter biomass, and a moderate amount of grass and forb biomass. This cluster contains 597 or 9.5% of the stands. The pine-mixed hardwood stands with relatively moderate litter biomass, low shrub biomass and little other fuel make up cluster 6 which has 131 or 2% of the stands. Finally, there is a 7th small cluster, very distinct in Fig. 2, resulting from swamp conditions on the SRS. This cluster 7 consists of baldcypress-tupelo (*Taxodium distichum–Nyssa aquatica*) stands, which typically have a very high shrub biomass component, and accounts for only 38 or about 1% of the stands. For averages and ranges of fuel loadings in these stands see Parresol et al. (2012). In Table 4 we see that the overall classification error rate is 9% or that 91% of the 6329 stands were correctly classified by the linear discriminant function. The discriminant analysis tells us that the clusters are indeed unique groups that are easily distinguishable based on their fire behavior characteristics. The error results from clusters overlapping slightly along their surfaces. Visual confirmation is provided by Fig. 2.

3.2. Fire behavior fuel models

From the clusters, centroid fuel values were computed (Table 5). Data from the stands with the closest Euclidean distance (Eq. (1)) to the centroid values, along with the ancillary data, were used to parameterize the Rothermel (1972) spread equation to create the 7 initial FBFMs. The calibration procedure required 63 FCCS runs (9 calibration points $\times$ 7 models) where ROS, FL, and fireline intensity (FLI) outputs were used to adjust the custom FBFM parameters.

We developed a custom spreadsheet application that implements Rothermel's surface fire spread model. The spreadsheet was designed to include calibration and adjustment factors for tuning the initial fuel model parameter values in order to get the simulations to match the FCCS data. The backbone of this tool is a set of three charts—one each for ROS, FL, and FLI—and a table of calibration/adjustment factors. Examples of the charts are given in Fig. 3 for cluster 1 or custom FBFM SRS-1. On the charts in Fig. 3 one can see the simulated behavior of the custom fuel model for a range of midflame wind speeds and all three fuel moisture scenarios. Superimposed on these lines are the nine calibration data points, with points for the same fuel moisture set connected by a line. The goal of the calibration exercise is to adjust fuel model

Table 3
Basic description of each cluster from Ward's minimum-variance hierarchical clustering method.

Cluster	Description	Fire behavior fuel model
1	Pine dominated – more litter than other clusters and high DWD biomass relative to other clusters	SRS-1
2	Combination of hardwood and pine stands – low to moderate reaction intensities, no shrub layer	SRS-2
3	Hardwood dominated – relatively low shrub biomass and cluster with the most non-woody and DWD biomass	SRS-3
4	Combination of pine and hardwood stands – relatively high non-woody biomass, substantial shrub and DWD biomass	SRS-4
5	Combination of pine and hardwood stands – relatively high shrub and litter biomass, moderate non-woody and low DWD biomass	SRS-5
6	Pine-mixed hardwood stands – relative to other clusters, moderate litter, low shrub, and little or no non-woody and DWD biomass	SRS-6
7	Baldcypress-tupelo stands – compared to other clusters, very high shrub, low litter and very little non-woody and DWD biomass	SRS-7

Non-woody means grasses and forbs; DWD means down woody debris.

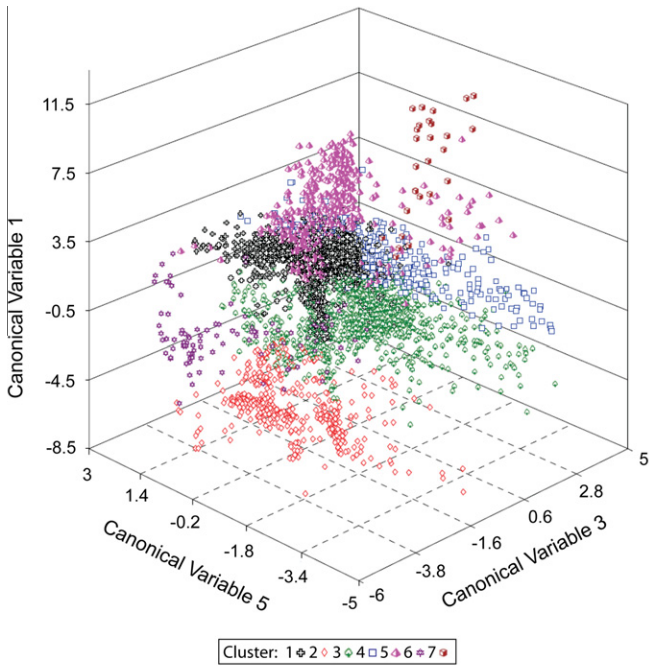

Fig. 2. Scatter plot of clusters in canonical space.

parameters to get the simulations to be as close as possible to the FCCS calibration runs. Each custom model was adjusted in turn, one at a time, manually. Goodness of fit was determined visually, not by any sort of least-squares measure. During calibration it became clear that no custom fuel model could be produced to match both ROS and FL/FLI at the same time while still matching the shape of the fire behavior response to wind speed. When ROS was good across a range of wind speeds and fuel moistures (Fig. 3a), FL and FLI were too high, compared to the FCCS outputs, by a factor of about two (Fig. 3b and c). In Rothermel's model, getting less FLI for the same ROS requires a shorter burning duration. Duration is a function solely of characteristic SAV ratio. Making the fuel particles finer (higher SAV ratio) results in shorter duration and consequently lower fireline intensity for the same ROS. Unfortunately, the large SAV ratio required to get ROS and FLI in the proper range drastically, and undesirably, changes the shape of the wind speed response of the fuel model. We could do either FLI or ROS well, or both very poorly. We chose the former option, and abandoned the idea of creating a single fuel model to replicate FCCS-simulated FLI and ROS at the same time. All calibrations were initially made to make FLI (and consequently FL) match as closely as possible (see Fig. 3e and f). When that was completed for all 7 fuel models, we computed the ratio of FCCS-simulated ROS to fuel-model simulated ROS (for high fire danger, 9.7 km h^{-1} mid-flame wind speed) and used this as a separate adjustment factor by which to get ROS calibrated. In Rothermel's model this can be simulated by multiplying all fuel loads and fuelbed depth by this same adjustment factor. This blind second calibration to ROS worked very well. All ROS calibrated fuel models were created in this fashion. The result of this procedure is two sets of 7 fuel models—one for accurately replicating FCCS FL and FLI, the other for accuracy in replicating FCCS ROS—and a set of adjustment factors that can be used in FARSITE, NEXUS, and other programs for getting both ROS and FL/FLI right in a single simulation.

We developed a spreadsheet application to facilitate comparison of the 7 custom Savannah River Site FBFMs. In Fig. 4 we see how these fuel models simulate fire behavior over a range of wind speeds (measured at a height of 6 m) using the high fire danger fuel moisture conditions (Table 1). In Fig. 4a we see the variation in ROS among the fuel models, with SRS-6 having the highest ROS and SRS-1 and 2 having the lowest and nearly identical ROS. In Fig. 4b we see the variation in flame length among the fuel models. FBFM SRS-1 exhibits the lowest FL ranging from about 0.3 to 1 m, very gradually increasing with wind speed. In contrast, SRS-6 exhibits fairly high FL increasing from 1 to 3.6 m across wind speed. Fuel models SRS-3, 4, and 5 behave similarly in regard to FL. Finally, in Fig. 4c we see the variation in FLI behavior with wind speed. Fuel models SRS-4 and 5 are very close and SRS-3 runs a little higher. Fuel model SRS-1 has the lowest FLI and SRS-6 has the highest FLI that rises sharply with wind speed.

Table 5
Centroid values for the clusters.

Cluster	ROS	RI_Shrub	RI_Nonwoody	RI_Woody	RI_LLM
1	6.6	2990.4	202.2	187.6	1861.3
2	4.4	3.1	193.8	27.1	1286.6
3	4.6	731.2	704.4	197.9	1194.2
4	6.3	3013.1	616.6	135.6	933.4
5	14.0	4596.7	259.2	62.0	1547.7
6	6.3	736.0	5.3	0.5	1247.7
7	31.1	9869.5	1.3	0.6	511.0

ROS is rate of spread in m min^{-1}. The prefix RI means reaction intensity in kJ m^{-2} min^{-1}. LLM is the litter–lichen–moss layer.

Table 4
Discriminant analysis result giving number of observations (top) and percent classified (bottom) into each cluster, and the classification error percent for each cluster.

From cluster	To cluster							
	1	2	3	4	5	6	7	Total
1	2580	0	66	164	0	5	0	2815
	91.65	0.00	2.34	5.83	0.00	0.18	0.00	100.00
2	0	509	9	0	0	16	0	534
	0.00	95.32	1.69	0.00	0.00	3.00	0.00	100.00
3	22	61	1378	99	0	18	0	1578
	1.39	3.87	87.33	6.27	0.00	1.14	0.00	100.00
4	69	0	2	540	25	0	0	636
	10.85	0.00	0.31	84.91	3.93	0.00	0.00	100.00
5	91	0	0	3	486	3	14	597
	15.24	0.00	0.00	0.50	81.41	0.50	2.35	100.00
6	0	0	0	0	5	126	0	131
	0.00	0.00	0.00	0.00	3.82	96.18	0.00	100.00
7	0	0	0	0	0	0	38	38
	0.00	0.00	0.00	0.00	0.00	0.00	100.00	100.00
Error	8.35	4.68	12.67	15.09	18.59	3.82	0.00	9.03

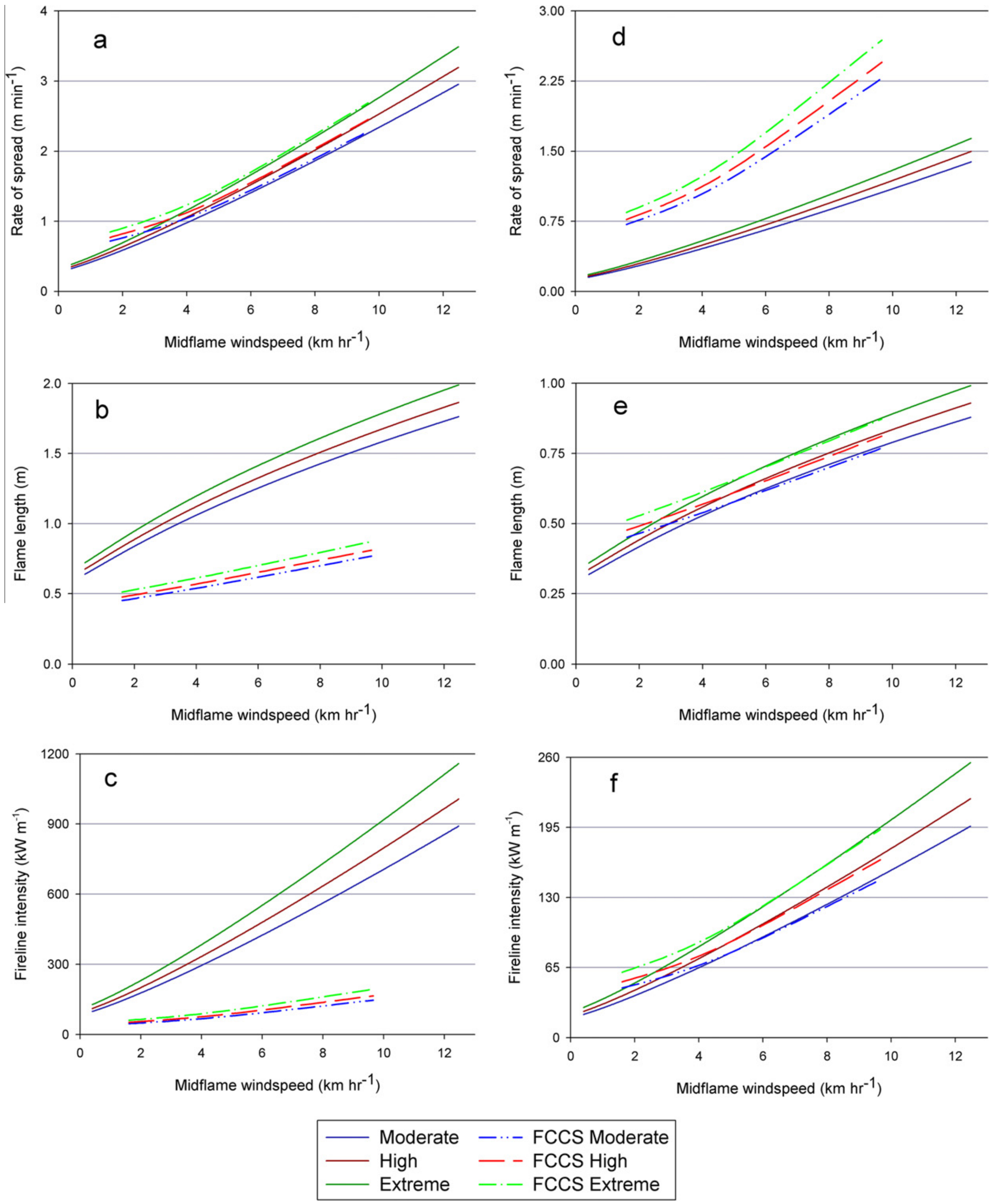

Fig. 3. Example calibration of fire behavior fuel model SRS-1 to FCCS fire behavior. The fuel model calibrated to FCCS rate of spread shows close correspondence to, (a) FCCS-predicted rate of spread, but lack of correspondence to, (b) FCCS-predicted flame length, and (c) FCCS fireline intensity. The fuel model calibrated to fireline intensity shows lack of correspondence to, (d) FCCS-predicted rate of spread, but close correspondence to, (e) FCCS-predicted flame length, and (f) FCCS-predicted fireline intensity.

4. Discussion and conclusions

4.1. Prediction

Cruz and Alexander (2010) and Cruz and Fernandes (2008) report a potential under prediction of surface fire behavior by the Rothermel (1972) wildland fire behavior model that relates to its sensitivity to the compactness of horizontally oriented surface fuels. The reformulation of the Rothermel model for FCCS addresses the issue of the variable compactness of different surface fuel layers by separating litter, which is typically much more compact, from the other surface fuels in most of the calculations related to surface fire behavior. In part, this was done to ameliorate the potential underprediction problem. The FCCS documentation (Prichard et al., 2011) points out that the main difference between the FCCS modeling approach and the Rothermel model is the treatment of more complex fuelbeds with four surface fuel strata. The litter, lichen and moss (LLM) stratum is generally

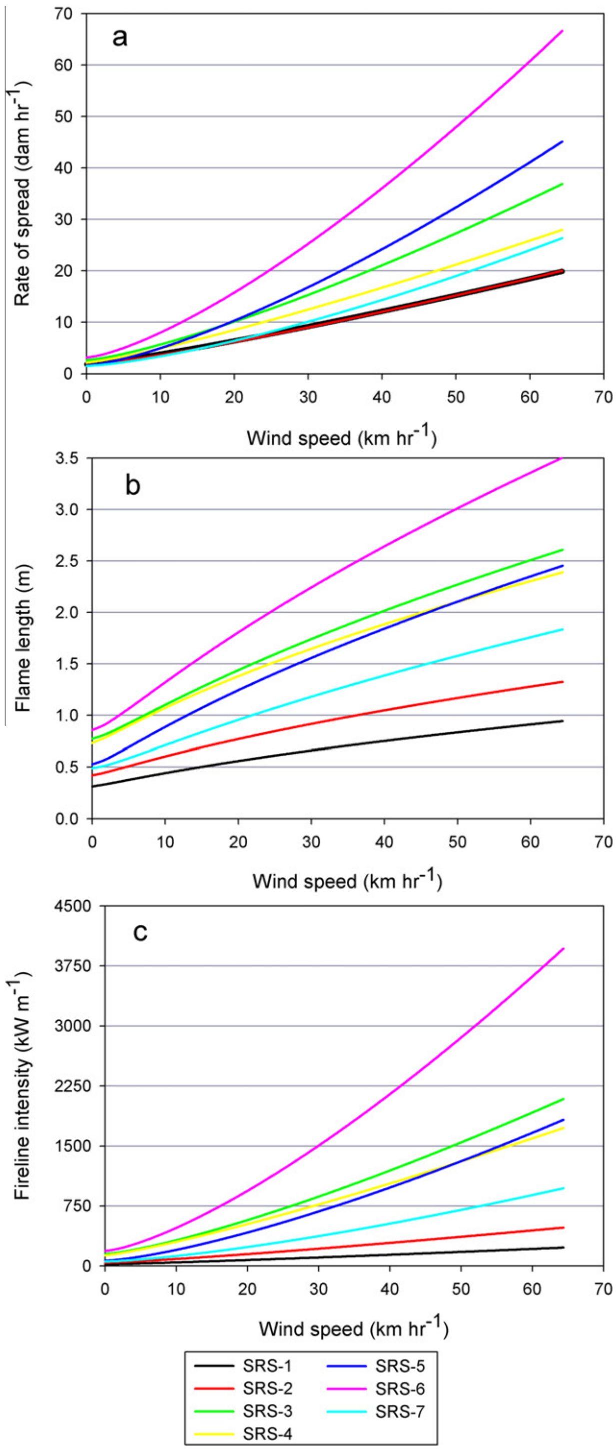

Fig. 4. Comparison of custom fire behavior fuel models for: (a) rate of spread, (b) flame length, and (c) fireline intensity over a range of wind speeds under high fire danger fuel moisture conditions (see Table 1).

much more densely packed and constitutes a different combustion environment than the other surface fuels (shrubs, non-woody fuels, and woody fuels). For this reason, the LLM stratum is treated separately from the other surface fuels. Therefore the FCCS model resolves the fire behavior contribution of heterogeneous mixtures of fuelbed categories within strata and mixtures of strata within surface layers, which addresses the criticism of Cruz and Fernandes (2008) and Cruz and Alexander (2010). Future field research should be conducted to compare the fuel and fire behavior characteristics of our fuel model clusters to measured fuel characteristics and observed fire behavior. However, that type of field assessment was outside the scope of our current study.

4.2. Fire spatial modeling

Geospatial fire modeling systems commonly used in fire planning and incident management, FARSITE and FlamMap, require FBFMs for use in the Rothermel (1972) surface fire spread model. Managing for fire hazard and treatment objectives often requires detailed site specific data. Because collection of field data requires significant time, methods for developing custom fire behavior fuel models from vegetation inventory data will help managers reduce costs while potentially improving modeling outputs. By clustering the stands (or ecological unit) using their fire behavior parameters, the resulting custom FBFMs can be mapped back to the landscape. This is a trivial GIS exercise because each stand on the landscape has one of the custom fuel models uniquely associated with it.

A major result of this study is that robust statistical methods can be applied to utilize a large number of fuel observations in order to characterize fire behavior, and that highly complex fuel conditions can be objectively reduced to a minimum tractable set of custom fire behavior models (Table 3 and Fig. 4) to facilitate landscape fire modeling. Results indicate that the custom models created from real data fall within the range of the standard fuel models typically used, but the predicted fire behavior of the area using the custom fuel models under extreme conditions is less than that of the standard models. These relationships are consistent with the measured fuelbed structures. Some of the variation can be related to differing fuel loads and stand structural differences.

4.3. Concluding remarks

The FCCS is a user-friendly and efficient platform for creating custom fuelbeds from inventory data that can then be used to characterize surface fuel components on a local or landscape scale and to generate fire behavior parameters that relate directly to the measured fuel values from the inventory (Ottmar et al., 2007; Andreu et al., 2012). Because cluster analysis had been successfully used to model fuels with reasonable precision over large areas (e.g., Poulos et al., 2007), it was logical to assume that fire behavior could also be handled in a similar manner. This study shows the validity of that assumption, as we were able to reduce ecologically variable and complex surface fuels to a tractable set of 7 FBFMs calibrated to FCCS point data for wind and fuel moisture conditions of the area. The FCCS has a proven track record of providing reasonable estimates for point fire behavior analysis (Ottmar and Prichard, 2012), in evaluating changes in fuelbeds and fire potentials (e.g., Youngblood et al., 2008; Zhang et al., 2010), and in particulate matter assessment (Munchak et al., 2011). Cluster analysis separated the data into distinct fire behavior fuel models (Fig. 2) that were readily interpretable (Table 3).

The methodology of the FCCS platform coupled with cluster analysis utilized for this project is applicable to a broader scale than the southeast US. Wildland fire is global in extent as are the issues and decisions faced by natural resource managers on fire hazard mitigation. This research establishes that large numbers of complex fuel structures can be arrayed within a manageable framework and reduced to create dynamic fire behavior models. Custom fire behavior landscapes can thus be created and fire potential evaluated in FlamMap or other similar type systems (Hollingsworth et al., 2012) to help determine risk and guide decisions in mitigation work. Future investigations with more detailed data, especially on fire behavior, are needed to modify and improve the current suite of tools used for fuels and fire analysis.

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