CSIRO PUBLISHING
www.publish.csiro.au/journals/ijwf International Journal of Wildland Fire 2009, 18, 315–325

# The wildland fuel cell concept: an approach to characterize fine-scale variation in fuels and fire in frequently burned longleaf pine forests

J. Kevin Hiers[A], Joseph J. O'Brien[B,E], R. J. Mitchell[A], John M. Grego[C] and E. Louise Loudermilk[D]

[A]Joseph W. Jones Ecological Research Center at Ichauway, Route 2, Box 2324, Newton, GA 39870, USA.
[B]USDA Forest Service, Center for Forest Disturbance Science, 320 Green Street, Athens, GA 30602, USA.
[C]Department of Statistics, University of South Carolina, Columbia, SC 29208, USA.
[D]School of Natural Resources and Environment, University of Florida, Gainesville, FL, USA.
[E]Corresponding author. Email: jjobrien@fs.fed.us

**Abstract.** In ecosystems with frequent surface fire regimes, fire and fuel heterogeneity has been largely overlooked owing to the lack of unburned patches and the difficulty in measuring fire behavior at fine scales (0.1–10 m). The diverse vegetation in these ecosystems varies at these fine scales. This diversity could be driven by the influences of local interactions among patches of understorey vegetation and canopy-supplied fine fuels on fire behavior, yet no method we know of can capture fine-scale fuel and fire measurements such that these relationships could be rigorously tested. We present here an original method for inventorying of fine-scale fuels and *in situ* measures of fire intensity within longleaf pine forests of the south-eastern USA. Using ground-based LIDAR (Light Detection and Ranging) with traditional fuel inventory approaches, we characterized within-fuel bed variation into discrete patches, termed wildland fuel cells, which had distinct fuel composition, characteristics, and architecture that became spatially independent beyond 0.5 $m^2$. Spatially explicit fire behavior was measured *in situ* through digital infrared thermography. We found that fire temperatures and residence times varied at similar scales to those observed for wildland fuel cells. The wildland fuels cell concept could seamlessly connect empirical studies with numerical models or cellular automata models of fire behavior, representing a promising means to better predict within-burn heterogeneity and fire effects.

**Additional keywords:** fire behavior, fire effects, fuel heterogeneity, *Pinus palustris*, prescribed fire.

## Introduction

Burn heterogeneity is critical in maintaining diversity in fire-dependent systems (Rice 1993; Williams *et al*. 1994; Collins and Smith 2006). Understanding fine-scale heterogeneity in frequent surface fire regimes is critical because it is the scale where most ecologically relevant fire effects are thought to occur (Rebertus 1988; Mitchell *et al*. 2006; Thaxton and Platt 2006). Currently, fuels and fire behavior are poorly understood at fine scales ($<10\,m^2$). Most studies have focussed on fire effects at larger spatial scales ranging from 10 $m^2$ to 10 000 ha (e.g. Hobbs and Atkins 1988; Turner *et al*. 1998; Finney 2001, 2004; Collins and Smith 2006). Variation of fuels within a fuel bed, however, can often exceed variation among fuel beds (Brown and Bevins 1986). Furthermore, burn heterogeneity in fire-dependent systems is often defined as only the mosaic of burned and unburned patches, not the variation in fire intensity within completely burned areas. As frequent surface fire regimes burn thoroughly, leaving no or few unburned patches, variation in fire intensity within burned areas is especially critical to predicting fire effects. Several investigators have suggested that this variation may be critical in regulating second-order fire effects including forest structure and plant diversity (e.g. hardwood mortality, seedling recruitment, and understorey species demography) (Rebertus 1988; Mitchell *et al*. 2006; Thaxton and Platt 2006).

High-frequency surface fire regimes support diverse ecosystems such as prairies, oak (*Quercus* L. spp.) woodlands and pine (*Pinus* L. spp.) woodlands. Longleaf pine woodlands of the south-eastern Coastal Plain (USA) have a frequent (1–5-year return interval), low-intensity surface fire regime that sustains high microscale understorey plant diversity with species richness as high as 50 species $m^{-2}$ (Walker and Peet 1984; Kirkman *et al*. 2004). Despite being characterized as having a continuous fuel bed (Scott and Burgan 2005), fine-scale variation in longleaf pine forest fuels and fire behavior may contribute to sustaining these high levels of plant diversity (Mitchell *et al*. 2006). Several species studied within this diverse assemblage have been documented to modify fire behavior as fuels (Rebertus *et al*. 1989; Robbins and Myers 1992). The extent to which heterogeneity in fire intensity at this scale explains variation in fire effects has been hypothesized but not tested (Thaxton and Platt 2006),

 10.1071/WF08084 1049-8001/09/030315

in large part owing to difficulty in measuring within-fuel bed variation and fire behavior.

Quantifying both fuel and fire heterogeneity at fine scales, however, has met with limited success, despite increasing evidence for its importance (Hobbs and Atkins 1988; Mitchell *et al*. 2006; Thaxton and Platt 2006). Presently, no standard procedures – or terminology – exist for characterizing fuels at scales smaller than stands or fuel beds. Fuel sampling typically quantifies fuel bed characteristics, requiring either coarse-scale methods (e.g. Brown transects) or averaging finer-scale sampling over the larger unit (Ottmar *et al*. 2003). Fernandes *et al*. (2000) documented numerous empirical studies that summarize within-stand fire behavior and fuel variation into burn unit averages. The recently published Fuel Characteristic Classification System (FCCS) (Ottmar *et al*. 2007; Riccardi *et al*. 2007) describes vertical heterogeneity within fuel strata to a finer level of detail than ever before, but the horizontal continuity of those strata is assumed constant within a fuel bed or forest stand.

The stand-level focus is in part due to the modeling tools used to estimate fire behavior. The most widely used fire prediction and fire effects models run on fuel data that are idealized into homogeneous fuel beds. For example, BEHAVE PLUS (Andrews *et al*. 2005) and FARSITE (Finney 2004) both assume homogeneity and continuity at scales finer than the fuel bed (Rothermel 1972). These assumptions imply that any spatial complexity within a given fuel type is inconsequential to fire behavior, but these generalizations have prevented important linkages between fire behavior and ecological fire effects. Furthermore, coarse, landscape-scale characterization of the fuels nationwide has become a focal priority (Keane *et al*. 2001). Attempts to model fires within heterogeneous fuels have been few and concentrated on mean fire behavior across the fuel bed rather than interactions of different fuel types (Frandsen and Andrews 1979; Catchpole *et al*. 1989).

Fire effects research hypothesizes important relationships between fine-scale fuel variation and fire in frequently burned ecosystems, yet has rarely characterized the variation in fuels or linked fuels to variation in fire behavior at a common scale. In their critique of contemporary fire ecology, Johnson and Miyanishi (2001) commonly found that fire effects researchers failed to properly quantify the fire environment that they suggest is directly influencing those patterns. Quantifying the fire environment has often focussed on visual estimates of flame length (Byram 1959; Rothermel 1972; Nelson and Adkins 1986; Fernandes *et al*. 2000). The dynamic nature of flames, often flickering at up to 10 Hz (Schultze *et al*. 2006), requires some integration that necessarily homogenizes flame-driven fire behavior measurements. Also, estimating flame length visually is inherently difficult because flames are often obscured by smoke (Fernandes *et al*. 2000). Finally, the fire effects of interest are not necessarily the flames themselves but rather the heating of vegetation, soils or fuels that are either involved in combustion or about to combust.

Studies of fire effects have often relied on point-measures of fire intensity to capture salient variation (Kennard *et al*. 2005). For example, fuels are characterized at larger scales but thermocouples or temperature-sensitive paints measure a point that requires error-prone spatial extrapolation (Iverson *et al*. 2004). The precision of these techniques for measuring fireline intensity is inadequate as thermocouples, thermal paints, and waxes often suggest temperatures lower than the combustion threshold and have significant measurement lags (Hobbs and Atkins 1988; Iverson *et al*. 2004; Kennard *et al*. 2005). Ecological studies have also used *post hoc* severity measures rather than linking fuels to fire (e.g. Rice 1993; Drewa 2003), but such approaches cannot be predictive of fire effects. Some of these shortcomings can be overcome with new technology, specifically digital infrared thermography, which can record precise temperatures over a wider spatially explicit area (Kennard *et al*. 2005). Given the important potential feedbacks between fuels, fire behavior and fire effects, measurements of fuels and temperature remain a basic bottleneck for rigorously testing these relationships.

In the present manuscript, we describe a strategy for synthesizing fuel and fire characteristics at the same scale using spatial statistics and then discuss the utility of our approach for better understanding both fire effects on ecological processes and fire behavior prediction. This approach quantifies and classifies fuel heterogeneity into groups at a range of scales from $<1\,m^2$ to $>10\,m^2$. We refer to these discrete patches as *wildland fuel cells* because they could be modeled as grid cells or pixels within the fuel bed, expounding on the term first used by Catchpole *et al*. (1989). We present here a novel, integrated methodology for characterizing wildland fuel cells as distinct aggregations of fuels particles within a fuel bed and corresponding fire behavior in longleaf pine forest fuels of the south-eastern United States. The distribution and arrangement of these wildland fuel cells captured variation that has definable properties such as height, volume, and bulk density, all of which are important determinants of fire behavior (Frandsen and Andrews 1979; Fujioka 1985; Andrews and Queen 2001; Scott and Burgan 2005), and likely varies at multiple scales among other forested ecosystems. We employed both remote sensing and direct inventories to characterized fuel structure and fuel spatial distribution at sub-metre scales, and statistically assessed the scale of fuel arrangement. Specifically, we tested the following hypotheses: first, are wildland fuel cells quantifiable and classifiable, and second, if so, at what scale are they arranged in longleaf pine ecosystems? We also tested whether the spatial variation among wildland fuel cells is significantly correlated with variation in fire behavior as measured by *in situ* infrared thermal imaging.

## Methods

### *Study areas*

The research study site was in frequently burned longleaf pine woodlands at Ichauway, an 11 000-ha reserve of the Jones Ecological Research Center in southwestern Georgia, USA. Ichauway is located within the Plains and Wiregrass Plains subsections of the Lower Coastal Plain and Flatwoods section (McNab and Avers 1994). Ichauway has an extensive tract of second-growth longleaf pine (*Pinus palustris* P. Mill.) and has been managed with low-intensity, dormant-season prescribed fires for at least 70 years, at a frequency of 1 to 3 years. The specific study site used had 1 year of fuel accumulation. The understorey is dominated by a diverse assemblage of grasses, forbs and sparse shrubs (see Outcalt 2000).

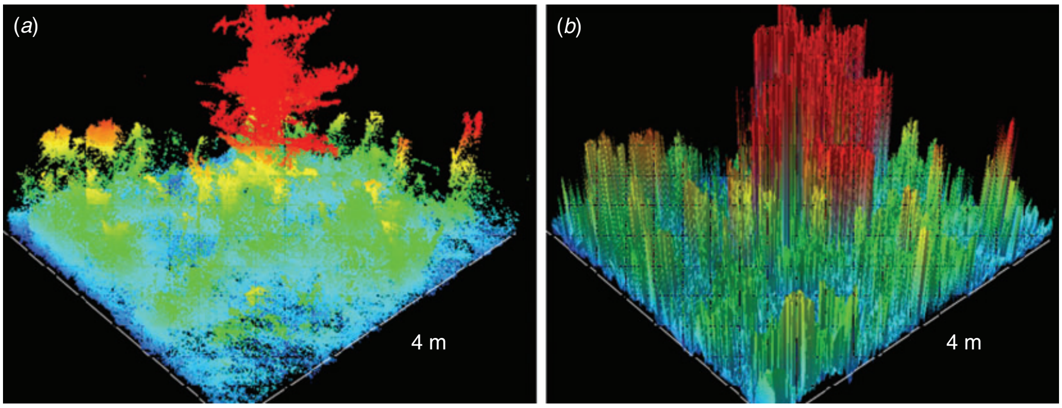


**Fig. 1.** Ground-based LIDAR (Light Detection and Ranging) image of 4 × 4 m plots: (*a*) sub-cm density point cloud illustrating the accuracy of this tool; and (*b*) Triangular Irregular Network (TIN) of LIDAR data used in spatial analysis and mapping of fuel bed heights.

### *Fuels inventory*

In early Spring 2007, a total of 30 surveyed 4 × 4 m plots were set up throughout the forest matrix with a goal to capture sub-metre variation in fuel bed characteristics across a range of overstorey structures (i.e. within forest gaps, along gap edges, etc.). The 4 × 4 m area was chosen because it was a large enough area to capture heterogeneity at sub-metre scales, but small enough to support intensive sampling with minimal impact to the vegetation. Spatially explicit point-intercept sampling data were recorded for each plot using a graduated dowel rod. We used 0.33-m spacing between point-intercept samples, including sampling along the edge of the plot, totaling 169 sample points within each plot. A ladder was suspended horizontally across each plot using saw-horses at each end to sample the interior of the plot, taking care not to disturb the vegetation. The sampling arrangement and intensity were performed to capture the spatial variation of the fuel bed found within this small (4 × 4 $m^2$) area and to relate to the centimetre-level 3D laser data collected from the ground-based LIDAR (Light Detection and Ranging). At each sample point, fuel bed and litter depth (i.e. height above ground in cm), as well as presence or absence of fuel and vegetation types were recorded.

As horizontal fuel continuity is an important predictor of fire behavior (Fernandes *et al.* 2000), but one of the most difficult fuel properties to measure (Brown 1981), we employed a mobile terrestrial laser scanner (MTLS) consisting of Optech's ILRIS 36D (Vaughan, ON, Canada) (Intelligent Laser Ranging and Imaging System) ground-based laser scanner to collect fuel heights and continuity. This LIDAR is mounted on a lift atop a mobile platform, increasing its versatility in capturing details about the terrain at multiple angles. The ILRIS uses a 1500-nm wavelength laser with a pulse frequency of 2500 points per second, recording first or last returns of each laser pulse (user-defined). The field of view is 40° in both horizontal as well as vertical planes. It has a range of 5 to 1500 m (at 80% reflectivity). The ILRIS has a pan-tilt base providing it a 360° rotation in the horizontal plane and approximately ±40° in the vertical plane. The lift makes possible the vertical movement of the scanner up to a height of ∼9 m. Mean point spacing of the laser data is user-defined, typically ranging from 1 mm to 3 cm (Fig. 1).

Within 2 weeks of field data collection, the MTLS collected ground-LIDAR data on all 30 plots. Prior to data collection, reference targets (consisting of a Styrofoam ball on top of a metal rod) were placed at all four corners of the plot. A double reference target (two Styrofoam balls on one metal rod) was used at the north-west corner of each plot to orient the plot for data processing. An additional one to four reference targets were placed just outside the 4-m plots to align LIDAR volume estimations with biomass clip plots. Biomass reference targets were placed in relatively homogeneous fuel types, with a circular area of 0.3 $m^2$. The MTLS was restricted to mapped roads and trails, as well as a buffer of 6 to 10 m around each plot, to reduce site degradation and vegetation disturbance. The ILRIS was lifted to 6- to 7-m height at each plot with a goal to capture as much of an aerial view as possible, without bole or canopy obstruction. The ability to vary the height and angle of the ILRIS (hence, using the MTLS) allows significant reduction in shadowing effects within the fuelbed that may be found when using the ILRIS on a tripod. The ILRIS was set to a downward angle tilt of 25° (from horizontal). A true color digital photograph was taken by the ILRIS for each plot, and used in the field to delineate the focus area. This eliminates any unnecessary data collection, enhancing efficiency in the field and reducing file storage size. First-return laser pulses were recorded with 5-mm mean point spacing. One scan was taken on opposite sides of the plot to further reduce shadowing effects and ensure more accurate and complete sub-cm data for both the 4-m and biomass plots. These two scans were merged in the processing stage to a single spatial coherent dataset. Data collection with the MTLS took ∼20 min per plot.

### *Fire behavior monitoring*

In each plot, we recorded fire behavior using an FLIR S60 digital thermal imaging system (FLIR Systems, Boston, MA, USA). The camera and operator were positioned on a boom ∼7 m above the ground and 10 m from the plot edge. Thermal images were captured as the fires burned through the plots at 0.25 Hz. The imager was coupled to a 0.5× lens to increase the field of view so each plot was captured in its entirety. The S60 records temperatures in each of 76 000 pixels per image (320 by 240 pixels) with a sensitivity of 0.06°C and accuracy of ±2%. The system is

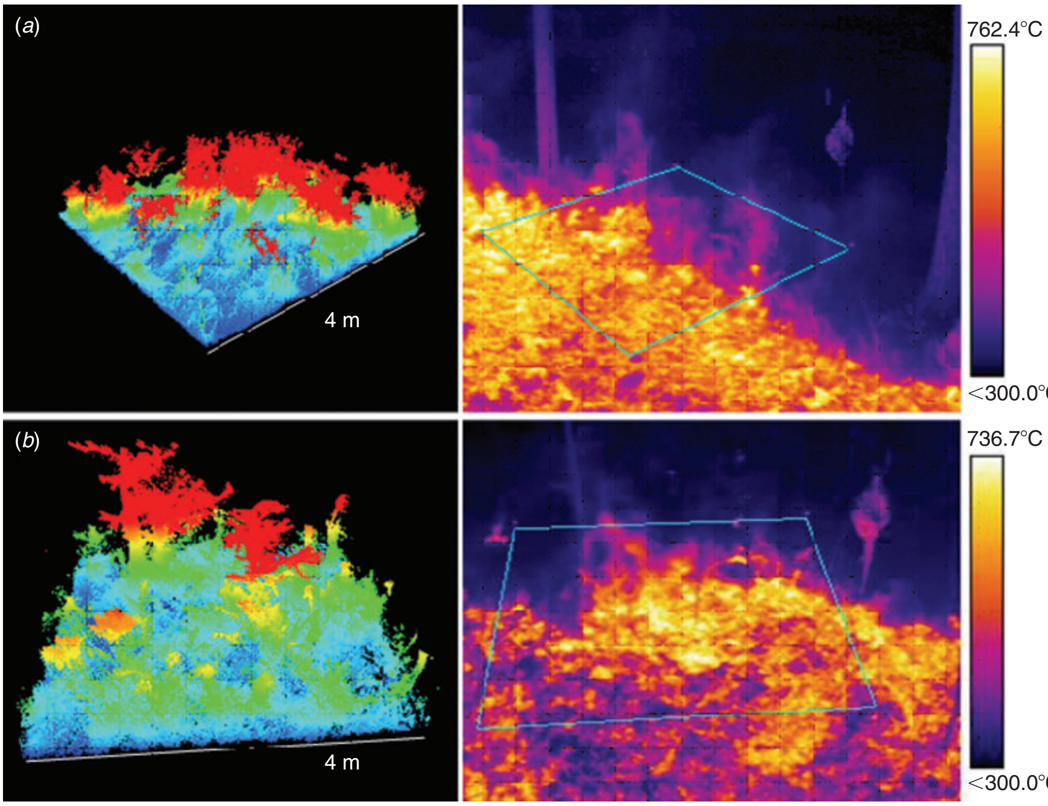


**Fig. 2.** Spatial data to delineate fuel cells required matching (*a*) LIDAR (Light Detection and Ranging) and (*b*) *in situ* thermal imagery of burns with georeferenced point intercept data of fuel characteristics.

capable of recording temperatures from −40°C to 1500°C. The camera calculates temperatures using measurements of emitted radiation with wavelengths between 7.5 and 13 μm. The measurements were corrected for air temperature, relative humidity, distance from target, and the emissivity was set at 0.96. A flare was placed at each plot corner and ignited immediately before the fires to provide surveyed reference points (Fig. 2). Fire images were analyzed using FLIR Systems' *ThermaCAM Researcher Pro* software version 2.7. Each image was then transformed into a tab-delimited ASCII file where each cell represented pixel temperature. These files were again transformed into TIFF files for post-processing, with the temperature data in these files captured as pixel color values. The TIFF files were rectified and georeferenced using image processing software (*IMAGINE*, *ArcGIS*).

### *LIDAR data processing and analysis*

LIDAR raw data consisted of a four-column text file containing *x*, *y*, *z* coordinates and laser return intensity values for each of the sampled laser points. Of the two scans taken per plot, the first was horizontally rectified by compensating for the original scanning geometry, where the instrument had a downward tilt of 25° with respect to horizontal. Using the common points (reference targets) and the process of 3D conformal transformation (Wolf and Ghilani 1997), both scans were combined into a single spatially coherent dataset. The merged dataset was then oriented in cardinal space using the double reference target (in the NW corner of the 4 × 4 m plot). The digital image and the double reference target for the NW corner of the plot were especially helpful in this merging process and in orienting the plot in cardinal space. The 4 × 4 m plot area and biomass plot areas were clipped from the resulting merged scans using the reference targets. Roughly 600 000 to 700 000 sample laser points were found within each 4 × 4 m plot. Point-densities, volume estimates, and height distributions were calculated for each biomass plot and each 4 × 4 m plot. Total volume ($cm^3$) was calculated in each plot by determining the presence or absence of laser points within each $cm^3$ space. The process involved using a 1-$cm^3$ window to move through each plot's point cloud in the *x*, *y*, and *z* directions respectively. Every time a point was (or points were) found in the 3D window, 1 $cm^3$ of volume was added to the volume counter for that plot.

### *Fire*

A total of 22 of 30 plots were burned in three prescribed burns conducted at an operational scale (∼70 ha each) using strip head fires on 23, 27 February and 16 March 2007. Fuel moisture was estimated gravimetrically every hour, and ambient weather conditions were collected with an on-site weather station. At all plots, 2-m microscale wind speeds and direction were sampled at two plots corners with self-contained, fire-resistant cup anemometers. Wind data were averaged every 4 s. A strip head fire was ignited 5 m upwind of each plot with > 100 m separating strip heads from downwind strips when plots were ignited. Plots within a burn unit were burned and sampled from downwind to upwind. Each operational strip head fire was allowed to burn through the plots unperturbed by additional lines of fire. Weather data were used as covariates in the analysis to isolate the effects of fuels on observed fire behavior.

### *Statistical analysis*

The point-intercept data for the study plots were converted to distance matrices for use in cluster analysis. Euclidean distances were used for continuous variables (fuel bed height, litter height), whereas asymmetric Jaccard distances were used for the 0–1 binary variables (presence or absence of longleaf pine litter, etc). Cluster trees were then calculated using the centroid method, and the number of clusters was selected based on the Cubic Clustering Criterion and Pseudo-F value traces (Everitt 1980). In the case of multiple local maxima for these criteria, the cluster groups were compared with known plot characteristics to select the final number of clusters (SAS Institute Inc. 2003). This process is similar to development of fuel beds at larger scales (Dimitrakopoulos 2002).

Summary statistics over time (represented by the multiple image captures by the camera) were computed for each pixel in the thermal imagery data, including maximum temperature, 90th quantile temperature (Q90), and residence time >500°C. The 90th quantile temperature data were used to analyze the thermal imagery because the lowest temperature measured on the camera's high-temperature setting was 300°C; thereby, Q90 distinguished unburned patches from smoldering fire. Screening models in the preliminary analysis also suggested that Q90 was the most sensitive to the fuel cell types developed from the cluster analysis, and thus this variable served as a thermal imaging response in all analyses.

Semivariograms were developed for the LIDAR height data and thermal imagery data for individually selected plots to determine the appropriate scale of wildland fuel cells for the present study. Histograms of pairwise distances provided insight into the spatial dependence among cells. Afterwards, smoothed curves were calculated for both the regular and robust semivariograms (Cressie 1993). These curves provide additional information on the scale of spatial correlation, and assist in the selection of a parametric model for the semivariogram, which could then be used in advanced modeling methods (SAS Institute Inc. 2003).

In order to analyze thermal imagery data or LIDAR data on the same scale as the point-intercept data, the data were smoothed using a narrow bandwidth smoother to maintain as many features of the original dataset as possible (Cleveland *et al.* 1992). For 22 of the 30 Ichauway plots, predicted values of fuel properties at each of the point-intercept coordinates (169 points per plot) were used as responses in exploratory analysis of the relationship between thermal imaging data and fuel cell types.

In this initial exploration, the thermal imagery data were analyzed using mixed effects models with fuel cell type as a fixed effect, and plot as a random effect (Handcock and Wallis 1994). Based on the semivariogram analysis, several types of spatial models were tested to study within-plot correlations for the random effect plot. To examine the overall spatial influence of wildland fuel cells on fire behavior, mixed effects models using 10 of the 15 available wildland fuel cells were applied

**Table 1. Characteristics of fuel cells using asymmetric Jaccard cluster analysis ($n > 2$)**
Heights are in centimetres

| Fuel cell ($n$) | Mean litter depth (cm) | Fuel bed depth (cm) | 10-h fuel (%) | 100-h fuel (%) | Perched pine (%) | Perched oak (%) | Wiregrass (%) | Other grass (%) | Shrub (%) | Volatile shrub (%) | Forb (%) | Bare soil (%) | Oak litter (%) | Pine litter (%) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. Wiregrass with perched pine litter (648) | 15.0 | 29.0 | 8.3 | 1.5 | 31.9 | 0.9 | 55.6 | 29.8 | 3.1 | 4.5 | 47.3 | 7.1 | 10.3 | 49.4 |
| 2. Graminoids, shrubs with perched pine litter (944) | 14.3 | 30.4 | 13.0 | 4.6 | 30.5 | 5.1 | 31.6 | 26.9 | 6.5 | 4.8 | 47.5 | 5.6 | 30.0 | 48.8 |
| 3. Forbs and other graminoids (11) | 15.3 | 19.8 | 14.1 | 2.4 | 27.9 | 0.9 | 28.4 | 46.4 | 2.3 | 7.3 | 44.5 | 5.2 | 10.6 | 54.1 |
| 4. Ruderal (57) | 2.8 | 9.7 | 10.5 | 5.3 | 8.8 | 3.5 | 7.0 | 33.3 | 5.3 | 0 | 29.8 | 5.3 | 29.8 | 28.1 |
| 5. Interstitial pine litter (177) | 4.5 | 5.9 | 10.2 | 2.2 | 19.8 | 1.1 | 28.8 | 21.5 | 1.7 | 4.0 | 17.5 | 4.5 | 10.7 | 66.7 |
| 6. Mixed litter (135) | 3.3 | 4.3 | 5.2 | 5.9 | 13.3 | 0.7 | 5.2 | 24.4 | 1.5 | 0.7 | 17.8 | 9.6 | 54.1 | 43.7 |
| 7. Flat pine litter (56) | 1.9 | 1.9 | 8.9 | 0 | 1.8 | 1.8 | 8.9 | 12.5 | 0 | 0 | 16.1 | 7.1 | 19.6 | 85.7 |
| 8. Shrubs with perched pine litter (743) | 19.3 | 34.0 | 9.3 | 1.2 | 42.3 | 2.6 | 42.0 | 50.5 | 7.3 | 5.0 | 47.5 | 7.0 | 17.9 | 36.9 |
| 9. Wiregrass with shrubs (914) | 21.1 | 48.9 | 8.1 | 1.5 | 39.6 | 5.0 | 72.5 | 39.8 | 8.5 | 1.8 | 44.0 | 15.2 | 25.4 | 36.9 |
| 10. Interstitial perched pine (98) | 9.1 | 12.7 | 9.2 | 0 | 45.9 | 1.0 | 52.0 | 28.6 | 2.0 | 2.0 | 24.5 | 13.3 | 20.4 | 61.2 |
| 11. Pine cones and woody debris (3) | 0 | 0 | 0 | 66.7 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 33.3 | 0 | 0 |
| 12. Bare soil (3) | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 100 | 0 | 0 |

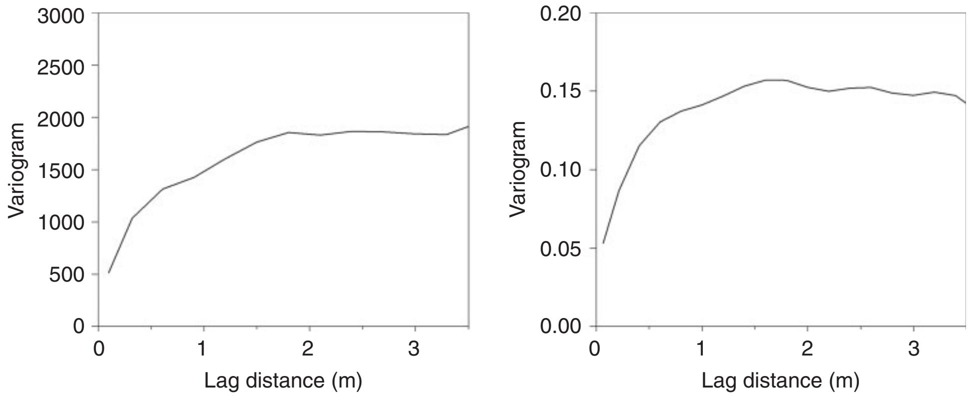


**Fig. 3.** Semivariograms of plot data show that both LIDAR (Light Detection and Ranging) and fire temperatures (90th quantile of temperature readings) both vary at sub-metre scales, as the sill is reached between 0.5 and 0.75 m in both cases.

to the 22 of the 30 Ichauway plots that received fire; the 90th temperature quantile was the response variable.

## Results

The results of the cluster analysis indicated fuel bed variation in the present study was captured by defining 15 discrete wildland fuel cells, 12 of which were represented by three or more samples across the 30 plots (Table 1). The wildland fuel cells represented a variety of fuel types ranging from patches of bare ground and coarse woody debris to complexes of pine litter, shrubs, and grasses. The most common wildland fuel cells in this study area were mixed graminoids, wiregrass with shrubs, and wiregrass with perched longleaf pine litter (Table 1).

These wildland fuel cells varied at small spatial scales. A semivariogram of LIDAR heights used to assess the patch size of fuels showed that wildland fuel cell heights became spatially independent beyond 0.5 $m^2$ (Fig. 3). This is a critical result for determining the appropriate scale at which fuels differ in this ecosystem. The distribution of wildland fuel cells also varied considerably among plots (Fig. 4). Of the 30 16-$m^2$ plots, the average number of fuel cell types per plot was slightly larger than two, with a maximum of five types and with eight plots dominated by a single fuel cell, although there was within-fuel cell variation in height in those plots. When multiple wildland fuel cells were present, the arrangement was often a mosaic pattern with patches and contours varying at scales $<1$ m (Fig. 4*b*).

Fuel cell type and their distribution across the plots had influence on fire behavior measures (Table 2, Fig. 4). In the mixed model used to assess the relationship of fuels and fire behavior, fuels cells were a significant predictor of fire behavior (90th temperature quantile, residence time and maximum temperature) across all plots independently of burn conditions ($P = 0.0024$, $F = 5.09$, numerator d.f. $= 9$, denominator d.f. $= 16$). Several methods were considered to model within-plot correlation between fire behavior and fuels, including non-spatial correlation models (independence and compound symmetry) and spatial models. The spatial models that included wildland fuel cells had much lower Akaike Information Criterion (AIC) values than the non-spatial models, indicating the importance of spatial relationships of wildland fuel cells in modeling within-plot correlations. Within the class of spatial models, those with Gaussian semivariograms worked best; this would be expected given the graphs of the empirical semivariograms (Fig. 3), in which the semivariograms increased quickly to a plateau.

Wildland fuel cells also interacted to influence fire behavior (Fig. 5). One conspicuous example of this interaction was a fuel cell of bare ground that caused a continuous fireline burning through other wildland fuel cells to form two parallel flanks. As the convective dynamics brought these two flanks together, an area of higher fire intensity and longer residence time was observed instead of the lower intensity that would have been expected if a single fire line had burned the fuel. The convective dynamics in the wake of slower-burning wildland fuel cells that dominate the heat contours of the plot (Fig. 4*a*) resulted in the decoupling of the direct relationship between maximum temperatures and downwind wildland fuel cells.

Although the analysis presented shows that the spatial models of wildland fuel cells are much better at predicting fire behavior than models without spatially explicit wildland fuel cells, the spatial model consistently overestimated effects of within-plot spatial correlation. Thus the model predicted that points $>1$ m apart were still strongly spatially correlated, contrary to observed data. Although two-dimensional variations in wildland fuel cells accounted for a significant proportion of the variation in fire behavior, additional modeling will be required to capture the fire behavior resulting from interactions among fuels cells.

## Discussion

These data are the first to statistically derive the relevant scale of variation in type (wildland fuel cell) and architecture (LIDAR) of within-fuel bed variation of fire-frequented forests. Although these fuel beds have been described as continuous (Scott and Burgan 2005), they show considerable heterogeneity of fuels and fire behavior at the sub-metre scale. We show that fuel beds are composed of distinct types of wildland fuel cells that differ in fuel properties (Table 1). Although we did not measure all the properties that influence the way that fuels might regulate fire intensity, such as density and chemical composition, we do show that type and fuel height can be discerned and significantly influence fire behavior at fine scales. As accurate fuel heights

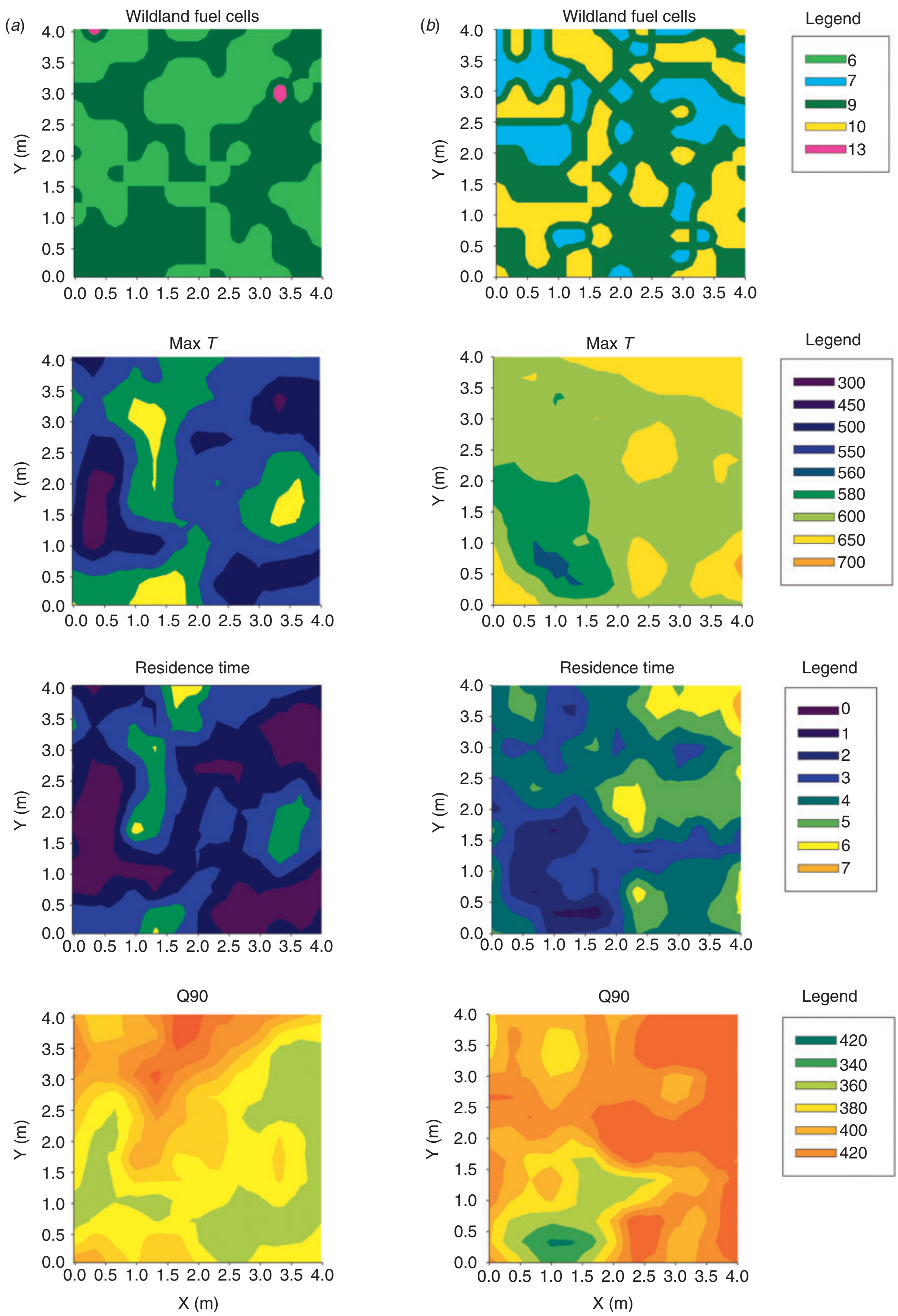


**Fig. 4.** Wildland fuel cell contours, maximum temperature, residence time (as a count of pixels >500°C), and 90th quantile temperature (Q90, °C) in sample plots 1 (*a*), and 35 (*b*). Wildland fuel cell legend refers to Fuel Cell Type; Max *T* legend refers to temperature in °C; Residence time legend refers to number of consecutive images that recorded temperatures over 300°C; and Q90 legend refers to temperature in °C.

**Table 2. Fire behavior in the wildland fuel cells referred to in Table 1**
Actual sample size refers to the number of times the fuel cell was encountered in each pixel within all plots

| Fuel Cell | Mean 90th quantile temperature (°C) | Mean maximum temperature (°C) | Mean frames >500°C | Actual sample size |
|---|---|---|---|---|
| 1 | 381.4 (80.3) | 540.6 (70.1) | 2.00 (1.13) | 648 |
| 2 | 349.2 (46.6) | 522.6 (77.7) | 1.96 (1.58) | 944 |
| 3 | 408.3 (100.3) | 530.2 (110.8) | 2.03 (1.47) | 210 |
| 4 | 384.5 (62.1) | 580.5 (73.2) | 2.40 (1.60) | 42 |
| 5 | 330.3 (45.3) | 480.6 (58.1) | 0.87 (0.76) | 177 |
| 6 | 335.3 (32.8) | 504.7 (62.0) | 1.38 (1.12) | 117 |
| 7 | 423.8 (48.6) | 588.2 (36.2) | 3.50 (1.04) | 56 |
| 8 | 374.6 (56.9) | 565.4 (73.6) | 2.05 (1.49) | 488 |
| 9 | 357.3 (61.6) | 547.5 (55.8) | 1.79 (1.11) | 764 |
| 10 | 425.3 (54.6) | 582.6 (41.5) | 3.04 (1.28) | 97 |
| 12 | 0 | 0 | 0 | 3 |

and thus volume have been a difficult measure to obtain in the field (Loudermilk and Cropper 2007), the approach described here has the potential for determining bulk density of fuels with greater precision than was possible with traditional methods. These characteristics can then interact with variation in understorey vegetation to create wildland fuel cells that are defined by their three-dimensional structure. For example, perched pine litter lying on wiregrass may burn more intensely or achieve higher maximum temperatures than a similar quantity perched among other vegetation, particularly forbs (Myers 1990). Also, fuel type has been reported to be important in these systems (oak *v.* pine litter) in determining fire behavior and fire effects at large scales (Williamson and Black 1981). Although the present paper does not address details of the relationship between wildland fuel cells and fire behavior, some predictable patterns emerged: the dominant vegetation type (Fuel Cell 1: longleaf pine needles and wiregrass) burned with greater intensity when contrasted with a similar fuel cell of old-field (historically plowed) vegetation (Fuel Cell 2); and although pine needles burned with high intensity (Fuel Cells 7 and 10), their presence alone does not have a uniform effect. It is also likely that wildland fuel cells that represent lower intensity and short residence times may be more important locations driving oak demography owing to their fire-sensitive morphology. One conspicuous shortcoming in the present work is the poor representation Fuel Cell 11, characterized by pine cones and pine branches (Table 1). The 30-cm point intercept grid as well as LIDAR missed many pine cones, which can burn with high intensity and long residence time (e.g. center and center left of Fig. 4*c*). Although these data were collected during a year without much pine reproduction, synchronized but episodic cone production occurs in longleaf (Boyer 1979) and may play an important but as of yet untested role in regulating plant community structure through influences on mortality and recruitment after fire. Thus the temporal changes in wildland fuel cells at small scales may also substantially influence fire behavior. Although it is beyond the scope of the current study to exhaustively explore fuel cell types and characteristics, the present work does show that (i) wildland fuel cells can be categorized and quantified; (ii) their spatial scale can be defined; and (iii) the latter properties can be related to fire behavior.

Conceptually, wildland fuel cells can connect fire heterogeneity and fire ecology in frequently burned forests because they represent a predictive link between fire behavior and effects. Previous attempts to model fire behavior required a generalized description of fuel bed characteristics at coarse scales (Finney 2004). The applicability of the knowledge gained from these scales, however, may be limited when applied to forests with frequent surface fire regimes that burn fuels thoroughly (Miller and Urban 1999). Even in forests with complete burns, spatial heterogeneity of fuels and subsequent fire have been shown to regulate forest structure, nutrient dynamics, and diversity (Lertzman and Fall 1998; Brown and Sieg 1999; Liu *et al*. 2005; Menges *et al*. 2006). The wildland fuel cell concept represents a synthesis of several different fuel characteristics, including type, quantity and arrangement, that can all influence fire behavior. In this way, they are conceptually analogous to ecological site units (Barnes *et al*. 1982), which are spatially explicit elements derived from analysis of species composition as well as site characteristics. Ecological site units emerge as discrete entities from a mass of complex multivariate data much as the wildland fuel cells do.

Last, numerical modeling- and physics-based approaches have made vast improvements by working with first principles of fluid dynamics (Linn *et al*. 2005), but have not been integrated with field studies to test assumptions and improve model performance. Detailed observations of fuels and fire behavior could further development of numerical modeling-based fire behavior prediction and extend them to help predict community response to fire. For this to occur, empirical studies that link fuels, fire behavior and fire effects are needed. The fuel cell method coupled with digital infrared thermography provides a novel and rigorous means of investigating these relationships. Also, if new physics-based models are going to be less computationally demanding, studies will be needed to explore how to make calculations more parsimonious, integrate heterogeneous fuels, and detect thresholds of fire effects. The fuel cell method

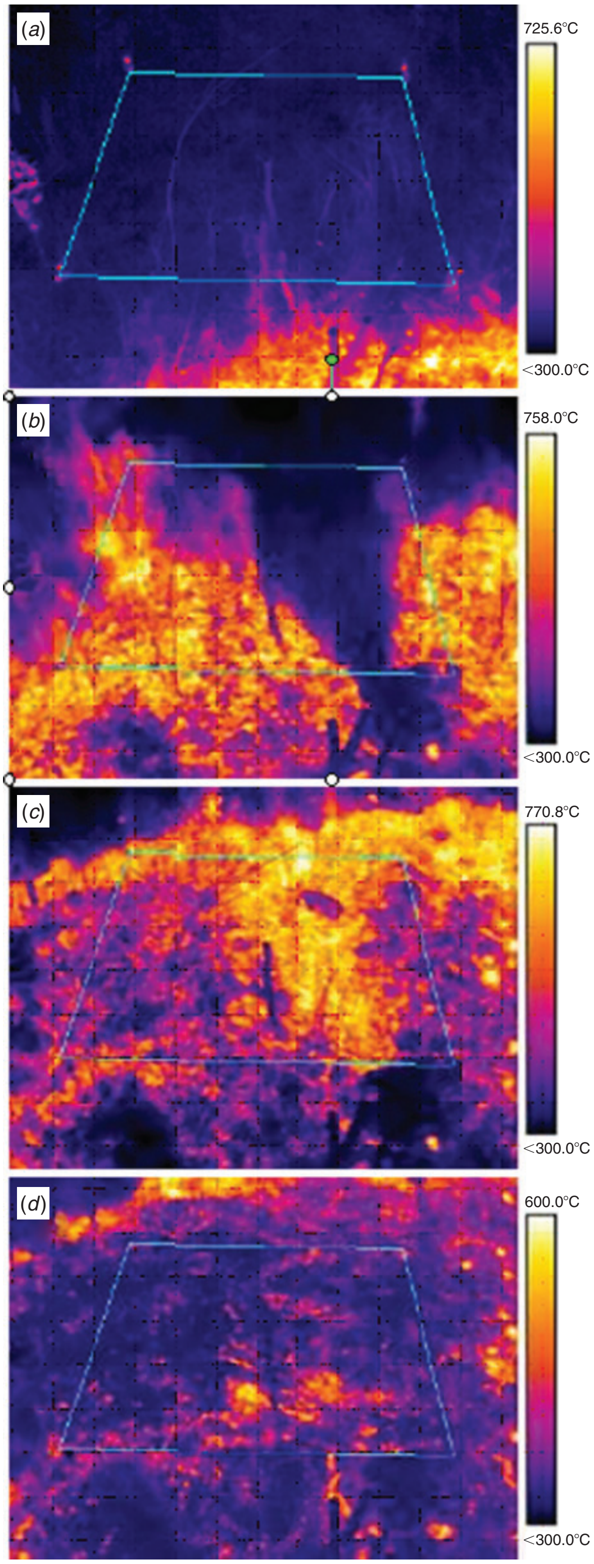


**Fig. 5.** Time series showing the interaction of fine-scale fuel variation and fire behavior in the wake of a pocket gopher mound (Fuel Cell 12: bare mineral soil). Interactions among wildland fuel cells are both critical and complex for predicting fire effects. (*a*) 23 February 2007 12:17:34; (*b*) 12:18:31; (*c*) 12:19:11; and (*d*) 12:21:42. Total elapsed time was 4 min 8 s.

provides an empirical setting that is inherently structured to be compatible for such research.

For these potentials to be realized, considerable work is needed on understanding how small-scale regulation of ecological effects can be expanded to scales relevant for land management. The high level of detail in the measurements reported here and used to define wildland fuel cells were necessary to explore the appropriate scales needed to explain the observed clustering of fuels and variation in fire behavior. Nonetheless, there remains a challenge in how to bridge the gap between the scales described in the current study, which vary from 1 to 5 $m^2$, and the scales relevant for wildland fire management, which range from tens to hundreds of hectares. This could be done by understanding the link between how larger-scale patterns of overstorey structure influence smaller-scale understorey patterns in vegetation (Mitchell *et al*. 2006).

In summary, our results show that fuel and fire behavior vary at similarly fine scales in frequently burned fuel beds. Understanding this fine-scale fuel heterogeneity and fire behavior is critical to predicting fire effects in these surface fire regimes because individual plant demography (recruitment and death) tends to occur at small scales, is complex in its interaction with fire and has proved to be difficult to study (Rebertus *et al*. 1989). These fine-scale patterns in fire intensity may be an important, and as of yet poorly explored, mechanism driving patterns in plant distribution through impacts on recruitment and mortality that otherwise might appear stochastic.

## Acknowledgements

Funding for the present work was provided by the Joseph W. Jones Ecological Research Center and the Robert W. Woodruff foundation as well as the USDA Forest Service Southern Research Station.

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Manuscript received 29 May 2007, accepted 1 July 2008