DEVELOPING ALTERNATIVE FUEL MODELS WITH WORLDVIEW-3 TO ESTIMATE FIRE BEHAVIOR IN A SEMI-DESERT GRASSLAND

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ABSTRACT

Developing fuel models to help predict fire behavior and hazard for desert grasslands is challenging due to the spatial and temporal variability of fine-fuels. We developed custom fuel models specifically tailored to semi-desert grasslands in southern Arizona and compared them to LANDFIRE (LF) fuel models. We used our own fine-fuel biomass and cover type layers developed from field plots and 2015 Worldview-3 and Landsat 8 satellite imagery using machine learning algorithms. We applied a rule-based approach to assign standard fire behavior fuel models from fuel data layers. LF (2001 and 2014) and custom fuel models (2015) were used in fire behavior software to compare 20 randomly assigned fire starts run under 90th percentile fire weather conditions. Custom models differed significantly from LF model outcomes showing up to 26 times greater fire size, particularly in areas with higher non-native plant cover. Modeled fire-line intensity and actual burn severity data from four wildfires and two prescribed burns indicated that the custom model more closely follows burn severity patterns within the study area. Semi-desert grasslands dominated by non-native perennial grasses with more contiguous fuel-bed structure are likely to experience larger fire size. Fuel models developed from data representing these conditions produced more realistic fire behavior that can improve targeting for fuel hazard mitigation and long-term efforts to restore native grassland composition. Accurate fuel models are critical for wildland fire management, they allow fire managers to determine how hazardous fuel conditions are, and the likelihood of a large fire that could endanger wildlife habitat and human infrastructure.

KEYWORDS: fire modelling, fire behavior, WorldView 3, semi-dessert grasslands

INTRODUCTION

Models describing the quantity and arrangement of combustible grassland fuels are vital to assessing potential fire behavior across large landscapes. Wildland fire remains an important ecosystem process essential to maintaining semi-desert grassland productivity, nutrient cycling and diversity in the Southwest (Brooks and Chambers 2001; Brooks and Minnich 2006). Knowledge about fine-fuel production and distribution also aids prioritizing hazard reduction through fuel mitigation designed to protect natural resource values and human infrastructure (Rollins 2009). Thus, fuel and predictive models are continuously sought to estimate the possible intensity and spread of fires to help direct management actions to critical areas.

In the US, a majority of fire behavior research has been dedicated to assessing montane and forest land fuel types (Bessie and Johnson 1995). Nevertheless, the amount and size of savanna and grassland fires can rival or potentially surpass that of forest and shrublands in some years (Zahng and Kondragunta 2008). In contrast to forest systems, tree canopy cover, bulk density, and base height are relatively unimportant to grassland fire rates of spread and fire-line intensity. Instead fine-fuel continuity, moisture and weather are critical drivers of fire behavior (Cheney et al. 1998). Semi-desert grasslands are dynamic in that fine-fuel production is mitigated by temperature, precipitation, plant community composition and time since prior disturbance (McDonald and McPherson 2011; Gray et al. 2014).

In southern Arizona, fire suppression, overgrazing, and prolonged drought have led to the invasion of grasslands by woody plants such as *Prosopis spp.* and non-native grasses such as *Eragrostis lehmanniana* and *Cenchrus ciliaris* (McPherson 1995). *E. lehmanniana*, a tufted bunchgrass from South Africa, can dominate landscapes and out-competes native grasses on many sites in southern Arizona. *E. lehmanniana* has lignified and persistent biomass that is often 3 to 4 times greater than native plant biomass and dramatically increases fine-fuel loads (Cox et al 1990). In response to precipitation in the cool season, *E. lehmanniana* produces a significant amount of new plant tissue and seed while native grasses are still senesced (Huang and Geiger 2008). Thus, non-natives can substantially increase grassland fuel loads and vulnerability to large fires that.

Surface fuel model layers for the nation are available through LANDFIRE (LF) and were developed for use with software such as FlamMap and FARSITE, where fire behavior can be modelled. Fuel layers are created from classifying vegetation into groups based on fuel type, fine-fuel load and extinction moisture (Scott and Burgan 2005). LF refreshed national data products in 2014, but focused mainly on changes in canopy cover and height values rather than fine-fuel loads (Nelson et al. 2013). While LF products are available nationally, a fuel model can be customized with appropriate field plot data and multi-spectral satellite imagery that is tuned to region- and vegetation-specific physiognomies.

Adequate fuel characterization representing conditions on the ground is frequently a limiting factor for developing robust fire behavior simulations. Fuel mapping is confounded by the high spatial variability of fuels (Keane et al 2001) and fine-fuels and fuel-bed conditions are often poorly represented at the spatial and temporal scale at which grassland fires occur. With this study, we sought to better characterize semi-desert grassland conditions from fine-fuels data developed from well-distributed field plots and satellite data that may more realistically represent potential fire behavior.

METHODS

Study Area

Buenos Aires National Wildlife Refuge protects 48,000 ha of semi-desert grassland in southern Arizona and was released from grazing pressure in 1985. It is situated 90km southwest of Tucson situated in the Altar Valley (31º41’N, 111º27’W) (Figure 1). Mean annual precipitation is 40cm that is distributed bi-seasonally with 40% occurring in July and August with most other rainfall taking place during the winter months. Native grasses include grammas (*Bouteloua* spp.), plains lovegrass (*Eragrostis intermedia*) and wild buckwheats (*Eriogonum* spp.) Lehmann lovegrass (*Eragrostis lehmanniana*), an exotic, is prevalent in upland areas at lower elevations. Velvet mesquite (*Prosopis velutina*) is widespread on deeper soils and along drainages, with rockier soils supporting sub-shrubs such as snakeweed (*Gutierrezia sarothrae*), burroweed (*Isocoma tenuisecta*) and cacti (*Opuntia* spp.).

Fuel Model Development

We sought to produce a set of fuel types that would integrate seamlessly with LF national data products, and compared our model to the LF 2014 fuels data layer which incorporates disturbances such as fire, land use, vegetation treatments, insect and disease impacts which occurred after 2001. LF fuel models were developed using a rule-based approach combining data from field-referenced plots, Landsat imagery, vegetation maps, biophysical and topography gradients (Keane et al. 2001; Rollins 2009). The fuel model depicts the Scott and Burgan (2005) Fire Behavior Fuel Model (FBFM40) classes which describes 40 classes of fuel type within grass, grass-shrub, shrub, timber-understory, timber litter and slash/blowdown categories, the same set of fuel models available in LF 2014.

To develop a model matching LF products, we first developed our own intermediate geospatial data products derived from field plots to predict fine-fuel biomass and fuel-type across the study area (Sesnie et al. 2018). These products included herbaceous biomass or ‘fine-fuel’ (kg/ha) and mapped vegetation classes from a total of $n = 239$ vegetation plots measured between 2014 and 2015. These data were combined with 2015 ‘leaf-on’ and ‘leaf-off’ WorldView-3 and Landsat 8 OLI satellite imagery to map fuel conditions. A subset of plots with biomass estimates ($n = 239$) from 2014 and 2015 were used to develop the fine-fuels layer using Random Forest regression tree models (Breiman 2001) that explained 65% of the variation. A vegetation cover layer showed 80% overall map accuracy from a Random Forest classifier, and comprised of the following classes: Barren, Exotic Grass, Forb/Herblands, Native Grass, Madrean Oak/Juniper, Mesquite mixed grass and woody plants, Upland Shrub, Shadow, Tree cover, Urban/developed , and Open water. For this study, we grouped land cover classes into simple lifeform categories defined as grass, shrub and tree for developing fuel models. Further details describing field sampling and data layers are provided in Sesnie et al. (2018).

We then developed a multiple criteria evaluation matrix to (Figure 1) to classify land cover into a particular fuel type; we created constraints on the 30m biomass, tree cover, grass cover, vegetation land cover, elevation, and aspect raster layers, specifying thresholds for each variable and spatially combining pixels that met the criteria of the Scott and Burgan (2005) fuel types. The final fuel model was then smoothed with a 3 x 3 majority filter to better represent the level of fuel continuity likely present on the ground to categorize fuel types.

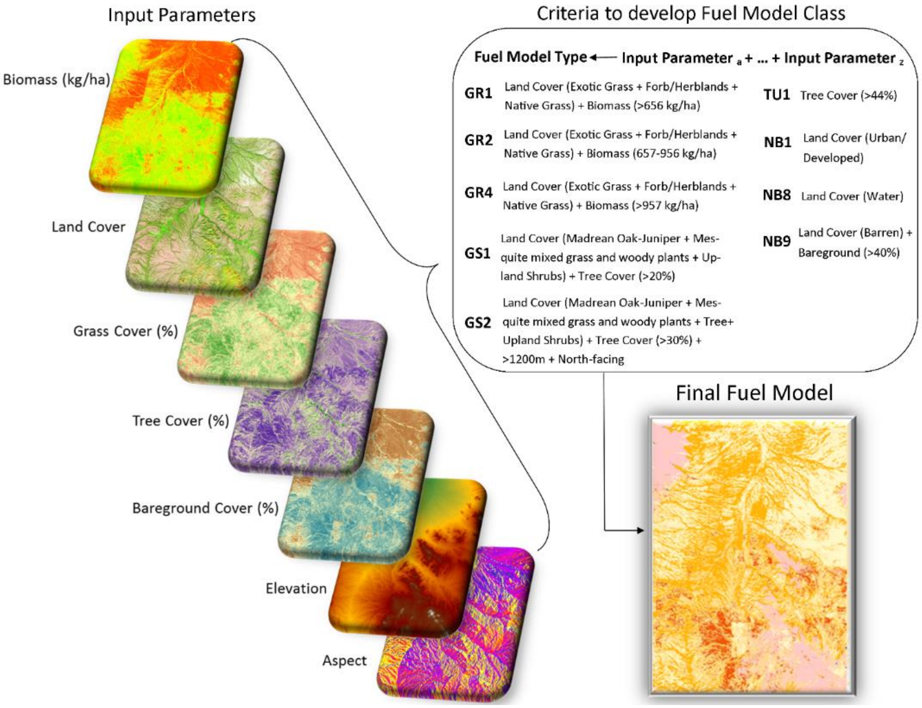


Figure 1. The conditional criteria for each fuel type varied in the spatial layers used, the inset box explains what layers were used for each fuel type, and what criteria was identified.

Statistical analyses and comparisons

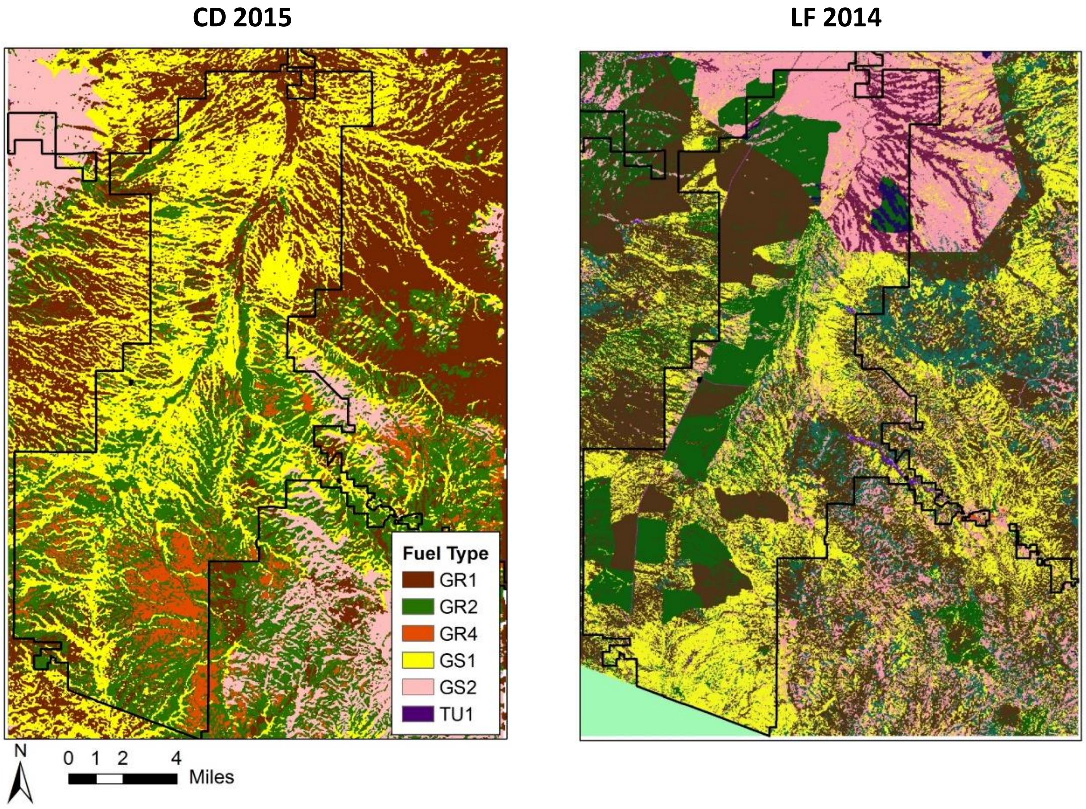
We compared fire simulations between LF 2014 and the custom-derived 2015 (CD 2015) fuel models to determine the degree of difference and potential for each fuel model to reflect realistic fire behavior. Simulations included fire weather, a fuel model, topography characteristics such as elevation, slope and aspect, and from Landfire: canopy cover, canopy height, canopy bulk density and canopy base height for areas with forest or woodland cover. Canopy fuel characteristics were not included for semi-desert fire simulations because the majority of the study area had little low tree cover. Fire weather from the middle of June, when 90% of fires occur in the area was used to simulate typical fire season conditions for this study site. Extreme fire weather conditions that can promote more extensive wildfires occur during the month of June. We used Fire Family Plus to determine average weather conditions over the last 10 years, downloaded from the closest RAWS station in Sasabe, AZ (021206). Associated air temperature, wind speed, wind direction and fuel moistures were input into FlamMap software v. 5.0 (https://www.firelab.org/project/flammap) to run simulated fires and predict fire size and intensity. Therefore, all aspects of fire simulations were held constant, with the exception of fuel model types for making fire behavior comparisons.

Twenty random ignitions were run on each model type: 1) LF 2014 and 2) CD 2015, at the same locations, spotting probability was set at 80% and burn time was set to 60 minutes, which is common for grasslands. The fires were set in FlamMap matching ignition points to actual burn scars to produce fire perimeters that most realistically matched, or exceeding actual burn perimeters. Wildland fire suppression techniques were unknown and would affect the total size of the actual fire, limiting comparability between burn perimeters of simulated versus actual fire data. Therefore, all simulations offered approximate fire behavior outcomes that were expected to burn more extensively in the absence of suppression activities.

RESULTS AND DISCUSSION

Fuel Model Comparisons

Visual inspection indicated that the fuel model layers differed substantially in spatial variability as well as dominant fuel types represented (Figure 2). The LF models have a more homogenous pattern when any prior disturbance was used to re-classify fuel types, which often follow management unit boundaries. LF 2014 models indicated that 40% of the refuge was a Grass 1 fuel model whereas only 3% fell into this category in the CD 2015 data layer. Most notable was that no areas were classified as a Grass 4 model by LF 2014 and a total of 25% of the refuge was consider a Grass 4 in the CD 2015 data. The CD 2015 also captured relatively high fine-fuel biomass conditions (≥ 900kg/ha) within continuous areas dominated by *E. lehmanniana* cover in the southern portion of the refuge.


CD 2015

LF 2014

Figure 2. Comparison of the CD 2015 model and LF 2014.

Fuel Model Performance: Random Ignitions

Higher fire-line intensity was found for the CD 2015 model because of the Grass-4 fuel model associated with high biomass levels, whereas the LF fire-line intensity layers show low values for much of the refuge at Grass-1 fuel model indicating fire spread would be low except in drainages and mountainous areas, where there were timber and shrub fuel types. CD 2015 simulations produced burned areas approximately 26 times greater than either of the LF models (Figure 3). The median hectares that burned for the LF 2014 was 60.4, compared with 1766.5 for the CD 2015 fuel model. The CD 2015 predicted fire sizes were significantly higher than the LF 2014 model ($p < 0.001$, t = 6.192). Simulated fires with the CD 2015 model ranged in size from 414 to 5645 ha with the largest fires occurring in the southern part of the refuge, which were dominated by *E. lehmanniana* cover. The CD 2015 fuel model consistently simulated larger fires across all 20 random ignitions, but the largest difference in size is in locations dominated by non-native perennial grasses that maintained high fine-fuel concentrations. This is consistent with Sesnie et al. (2018) findings where a positive relationship between biomass and non-native cover ($r^2 = 0.58$, F-stat = 13.14, $p<0.001$) occurred within fire management burn units.

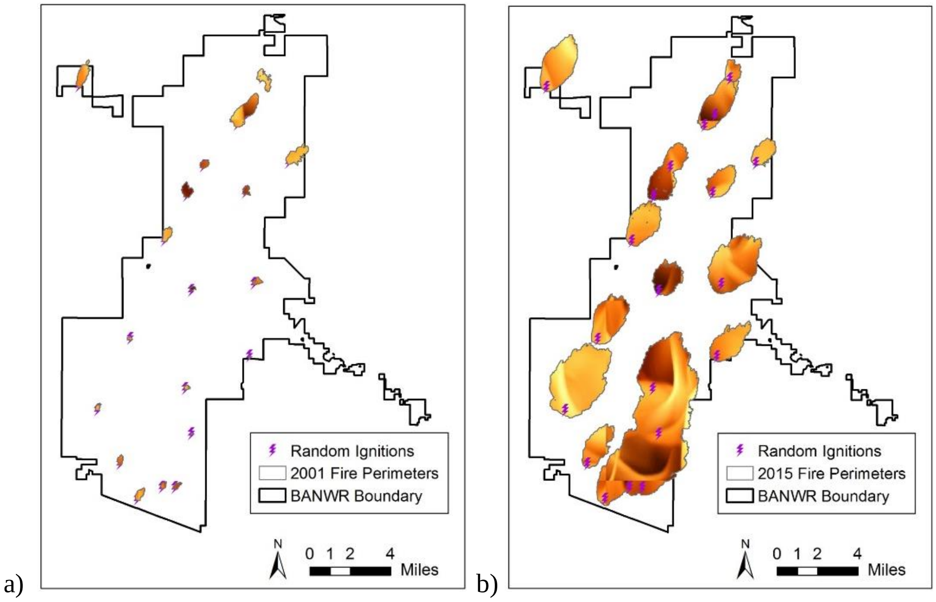


Figure 3. Extent of fire area predicted from random ignitions using a) LF 2014 fuel model and b) CD 2015 fuel model.

CONCLUSION

We used spatial data layers describing fine-fuels and vegetation cover developed from Worldview-3 and Landsat 8 satellite imagery and field plots to define fuel models within study area. While our approach was data-intensive, well designed vegetation inventories and monitoring data can and should be a part of routine land management activities on National Wildlife Refuges and other public lands. This is particularly important in fire prone areas where fire and fuels hazard mitigation are management are a priority. The CD 2015 fuel model reflect increased biomass from non-native plants across BANWR that were important to making realistic predictions of potential fire behavior. Given the spatio-temporal variability of precipitation in desert grassland that drives fine-fuel production, it is critical that fuel models remain up-to-date with the use of routine field measurements and available satellite data. Updated fuel models enhance fire management decision making by estimating semi-desert grassland fuel conditions and potential fire behavior. Thus, valid models of fire behavior are feasible and an essential to land management planning in fire-prone areas. We found fire behavior simulations were helpful for determine where prescribed and naturally occurring fires may help reduce hazardous fuel conditions or where other approaches may be necessary to retain values such as critical wildlife habitat and water resources.

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