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A comparison of four spatial interpolation methods for modeling fine-scale surface fuel load in a mixed conifer forest with complex terrain

Chad M. Hoffman[1]*, Justin P. Ziegler[1], Wade T. Tinkham[1], J. Kevin Hiers[2]; Andrew T. Hudak[3]

[1] Department of Forest and Rangeland Stewardship, Warner College of Natural Resources, Colorado State University, Fort Collins, CO 80523, USA, {c.hoffman, justin.ziegler, wade.tinkham}@colostate.edu
[2] Tall Timbers Research Station, Tallahassee, FL 32312, USA, {jkhiers@talltimbers.org}
[3] USDA Forest Service Rocky Mountain Research Station, Moscow, 80521, USA;

**Corresponding author*

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Abstract

Forest fuel inventory, monitoring and mapping provide the basis for fuel management activities, including assessing wildfire hazards and risk, prescribed fire planning, designing silvicultural treatments, and predicting fire behaviour and effects at various scales. One of the most significant challenges in developing accurate surface fuel maps is capturing the spatial variability of fuel load within and between different fuel components. In this paper, we compare the performance of four spatial interpolation methods for estimating and mapping fine-scale fuel load in a dry mixed conifer forest in Colorado, USA. The four approaches are: classification, multiple linear regression, ordinary kriging, and regression kriging. We chose these methods because they are commonly used in ecological studies and cover a range of SIM including, non-geostatistical, geostatistical, and hybrid approaches. All SIM methods yielded unbiased fuel load estimates, with mean error within 3% of the observations with MAPE from 100% to 40%, depending on the specific fuel com-ponent and spatial interpolation method. Our results indicate that regression kriging was able to better capture the fine-scale spatial variability in fuel load compared to other spatial interpolation methods.

1. Introduction

Forest fuel inventory and monitoring provide the basis for fuel management activities, including assessing wildfire hazards and risk, prescribed fire planning, designing silvicultural treatments, and predicting fire behaviour and effects at various scales. The most commonly assessed attribute of the fuels complex is the load. Fuel load is a required input to nearly all fire behaviour and effects models and is a critical component of terrestrial carbon inventories and wildlife habitat assessment (Keane et al. 2013). Fuel inventory approaches have traditionally assumed that the spatial variability in fuel load is of little consequence for management decisions and thus focus on providing estimates of spatially averaged values for a given area. Yet, recent studies highlight that fine-scale variability in the fuels complex exerts considerable influence on many ecologically relevant fire behaviour and effects metrics (O'Brien et al. 2016). Directly mapping fine-scale fuel variability is costly and time-consuming, especially across large. To overcome these limitations, it is often necessary to utilize a spatial interpolation method (SIMs) to estimate the fuel load at unsampled locations and generate spatially continuous fuel load maps for wildfire hazard and risk assessments, prescribed fire planning, and silvicultural treatment design.

One of the most significant challenges in developing accurate surface fuel maps is capturing the spatial variability of fuel load within and between different fuel components. This variability arises due to interactions between the physical environment (e.g., climate, soils, and topography) and ecological processes (e.g., productivity, deposition, decomposition, and disturbances) that determine the balance between inputs and outputs of fuel across multiple spatial and temporal scales. One of the most commonly used approaches to capture this variability is to classify an area into unique groups using auxiliary, often remotely sensed data (e.g., vegetation type, topographic data, or land use classes) and then assign a fuel load to all areas of a given class based on the sampled data (e.g., Keane et al. 2013). A drawback of a classification approach is that the variability in the data is reduced to a few unique values. Other researchers have utilized regression-based approaches where the relationship between continuous auxiliary variables and the surface fuel load is used to predict values at unmeasured locations. Previous studies have weak to nonexistent correlations between the surface fuel load and topographic and forest structural metrics (e.g., Lydersen et al. 2015; Hall et al. 2006) indicating that surface fuel maps developed based on these relationships may have limited accuracy. Recent studies have found that surface fuels exhibit strong fine-scale spatial autocorrelation, which, if taken into account, may increase fuel map accuracy (Keane et al. 2013; Vakili et al. 2016). Although previous research has acknowledged spatial autocorrelation in fuel load, only Pierce et al. (2009) have explicitly assessed the degree to which this improves spatial interpolation. Their results indicate that including spatial autocorrelation did not significantly improve fine-scale predictive accuracy compared to linear regression approaches. However, the scale of analysis used in this study was greater than the inherent spatial scale of surface fuel variability identified by Keane et al. (2013) and Vakili et al. (2016), which may have limited any potential improvements in predictive accuracy.

In this paper, we compare the performance of four SIMs for estimating and mapping fine-scale fuel load in a dry mixed conifer forest in Colorado, USA. The four approaches were: classification, multiple linear regression, ordinary kriging, and regression kriging. We chose these methods because they are commonly used in ecological studies and cover a range of SIM including, non-geostatistical, geostatistical, and hybrid approaches.

2. Methods

2.1. Study Area and Data Collection

We conducted this study on the 17.6-ha Pike Peak Forest Dynamics Plot (PFDP) located within the Pike and San Isabel National Forest of Colorado. PFDP was established in the summer of 2016 as a collaboration between Colorado State University and the USDA Forest Service for long-term forest dynamics monitoring. The PFDP is representative of mixed conifer forests in the southern Rocky Mountains with an elevation range from 2,781 to 2,833 m and a dry, continental climate with 660.7 mm of rain per year and a mean daily temperature ranging from -4.7° C in January to 14.0° C in August. Topographically, the PFDP is shaped by two significant ridges, one oriented west-east in the northern portion of the plot and another oriented northwest-southeast in the southwestern portion, and several smaller secondary ridges protruding from the two main ones. The dominant overstory vegetation for the study site includes ponderosa pine (Pinus ponderosa Lawson & C. Lawson) and quaking aspen (Populus tremuloides Michx.) on southern aspects, and mixtures of Engelmann spruce (Picea engelmannii Parry ex Engelm.), blue spruce (Picea pungens Engelm.), and Douglas-fir (Pseudotsuga menziesii (Mirb.) Franco) on northern aspects. The average density, basal area, and quadratic mean diameter at breast height for the site are 804 trees ha-1, 7.55 m2 ha-1, and 19.0 cm, respectively.

All trees in PFDP at least 1.37 m tall were mapped to the nearest 0.1 m and had their species, diameter at breast height, height, and crown base height recorded. To characterize the surface fuel load across the site, we double sampling procedure to estimate the fuel load of the 1-, 10-, and 100-hr dead down and woody fuels on 437 1-m2 irregularly located plots (Keane and Dickinson 2007, Tinkham et al. 2016). We estimated litter and duff fuel load using the depth-to-load method using locally derived bulk density estimates. Total fuel load was estimated by summing the individual component fuel loads (1- 10-, 100-hr dead, down and woody fuel, and litter and duff).

We used our stem-mapped overstory data along with remote sensing imagery to calculate two overstory (dominate species and basal area) and two topographic (percent slope and Beer’s aspect) characteristics that we used as auxiliary information in spatial interpolation. Topographic auxiliary variables were calculated using a 10-m digital elevation model (DEM; available at nationalmap.gov; accessed 20 June 2022).

2.2. Spatial Interpolation Methods and Analysis

We compared the performance of four SIMs for estimating and mapping fine-scale fuel loads: classification (CL), multiple linear regression (LR), ordinary kriging (OK), and regression kriging (RK). For LR and RK, we included local basal area, cover type, aspect, and percent slope as auxiliary variables. The CL model was based solely on the predicted cover type. For OK and RK, we predicted each fuel component separately with fitted auto-semivariograms.

We assessed the comparative performance of each SIM with a k-folds cross-validation approach. We chose the following statistics to assess SIMs’ performances: mean error (ME); mean absolute error (MAE); mean absolute percent error (MAPE); and Pearson’s correlation coefficient between observed and predicted values.

3. Results and Discussion

All SIM methods yielded reasonably unbiased fuel load estimates, with mean error within 3% of the observations (Table 1, Fig. 1). Except for RK predictions for the total fuel load, all approaches resulted in a slight underprediction bias. Although a minimal bias was associated with all SIM, OK consistently resulted in the greatest bias.

Table 1. Summarization of cross-validation from spatially interpolating surface fuel components' loads in the Pike Forest Dynamics Plot.

Component	Method	ME	MAE	MAPE	$r_{obs,pred}$
1-hour	CL	0.001	0.192	67%	0.36
	LR	0.001	0.193	68%	0.40
	OK	0.007	0.185	65%	0.38
	RK	0.004	0.180	63%	0.44
10-hour	CL	0.001	0.468	70%	0.13
	LR	0.001	0.480	72%	0.11
	OK	0.010	0.451	68%	0.24
	RK	0.004	0.454	68%	0.27
100-hour	CL	0.005	0.963	111%	0.09
	LR	0.005	0.966	111%	0.07
	OK	0.011	0.899	104%	0.23
	RK	0.001	0.894	103%	0.23
Litter	CL	0.000	0.143	50%	0.14
	LR	0.000	0.142	50%	0.15
	OK	0.000	0.134	47%	0.32
	RK	0.000	0.130	45%	0.40
Duff	CL	0.004	1.119	58%	0.55
	LR	0.004	1.082	56%	0.56
	OK	0.022	1.006	52%	0.60
	RK	0.001	0.973	51%	0.63
Total	CL	0.012	2.090	48%	0.43
	LR	0.011	1.830	46%	0.48
	OK	0.061	1.960	49%	0.36
	RK	-0.006	1.740	43%	0.53

The MAPE varied from over 100% to around 40%, depending on the specific fuel component and spatial interpolation method (Table 1). The two Kriging based approaches evaluated produced lower MAPE than either CL or LR, with RK producing the lowest MAPE across all fuel components. However, there were relatively small differences in MAPE among the SIM, with the best-performing SIM reducing MAPE between 2 and 8% compared to the worst-performing SIM. The Pearson Correlation coefficients ranged from 0.07 to 0.63, depending upon the fuel component and SIM. RK resulted in the greatest Pearson correlation coefficient of all SIM tested regardless of the fuel component.

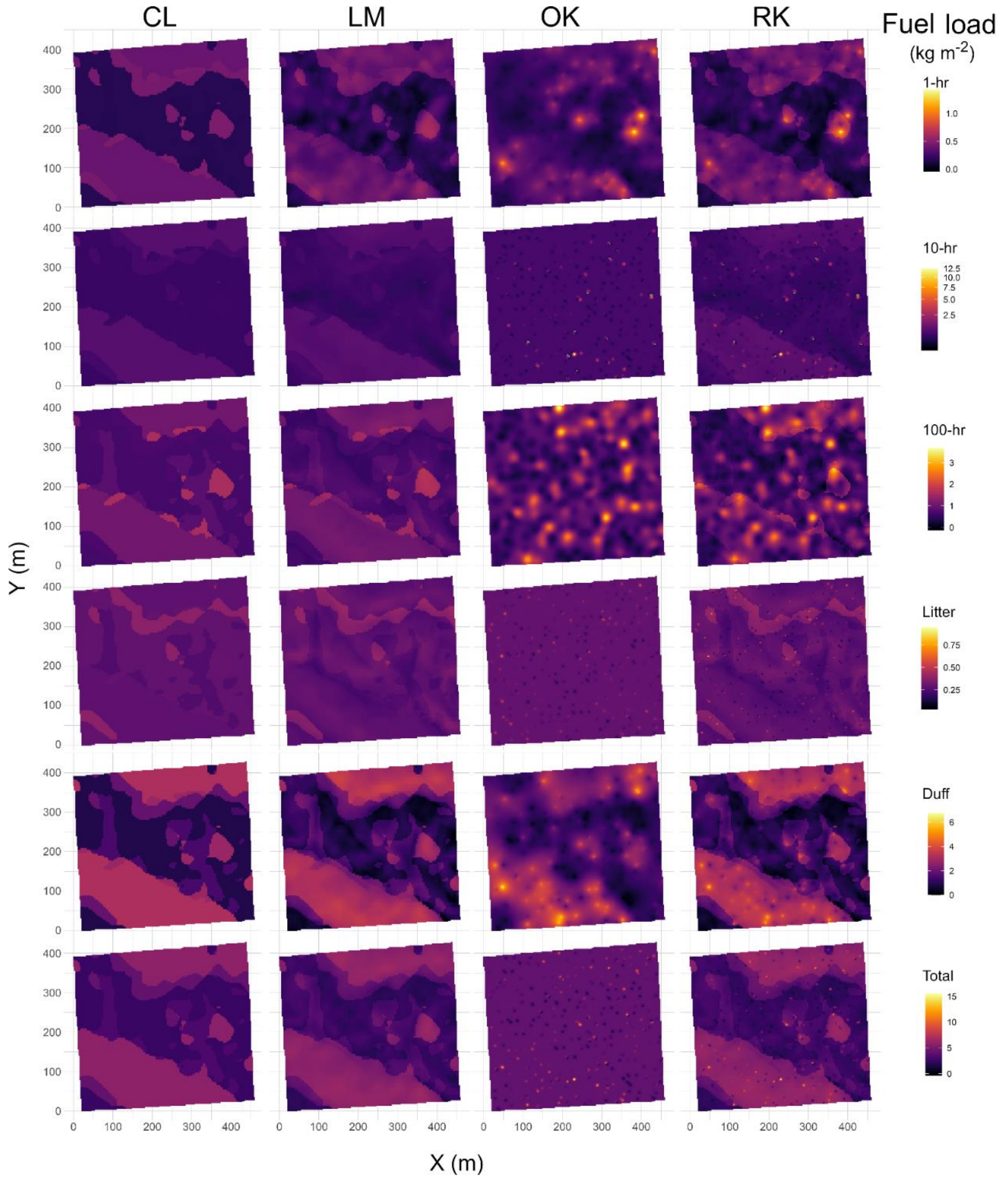

Fig. 1 Fuel load maps predicted in the Pike Forest Dynamics Plot by four spatial interpolation methods of 1-hour, 10-hour, and 100-hour woody fuels, litter, and duff surface fuel components, and total fuel load.

Fuel maps are commonly utilized by fire and land managers across a range of spatial scales to assist with fire suppression planning, locating and designing wildland fuel treatments, evaluating fire hazard and risk. Fine scale variation in fuel characteristics is increasingly recognized as important driver of fire behaviour and effects and as such, there is a growing demand for high-resolution maps of the wildland fuels. Of the four SIM evaluated, regression kriging provided the best overall estimation of surface fuel load for all fuel components. our findings indicate that RK was able to better capture the fine-scale spatial variability in fuel load and therefore is the preferred method to produce spatially interpolated fine-scale fuel maps.

4. References

Keane RE, Dickinson LJ (2007) The photoload sampling technique: from downward-looking photographs of synthetic fuelbeds. USDA For Serv Rocky Mt Res Station Gen Tech Rep RMRS-GTR-190

Keane RE, Herynk JM, Toney C, et al (2013) Evaluating the performance and mapping of three fuel classification systems using Forest Inventory and Analysis surface fuel measurements. For Ecol Manage 305:248–263. https://doi.org/10.1016/j.foreco.2013.06.001

Lydersen JM, Collins BM, Knapp EE, et al (2015) Relating fuel loads to overstorey structure and composition in a fire-excluded Sierra Nevada mixed conifer forest. Int J Wildl Fire 24:484–494. https://doi.org/10.1071/WF13066

O'Brien JJ, Loudermilk EL, Hiers JK, et al (2016) Canopy-Derived Fuels Drive Patterns of In-Fire Energy Release and Understory Plant Mortality in a Longleaf Pine (Pinus palustris) Sandhill in Northwest Florida, USA. Can J Remote Sens 42:489–500. https://doi.org/10.1080/07038992.2016.1199271

Pierce KB, Ohmann JL, Wimberly MC, Gregory, M.J., Fried, J.S. (2009) Mapping wildland fuels and forest structure for land management: A comparison of nearest neighbor imputation and other methods. Can J For Res 39:1901–1916. https://doi.org/10.1139/X09-102

Tinkham WT, Hoffman CM, Canfield JM, et al (2016) Using the photoload technique with double sampling to improve surface fuel loading estimates. Int J Wildl Fire 25:224–228. https://doi.org/10.1071/WF15027

Vakili E, Hoffman CM, Keane RE, et al (2016) Spatial variability of surface fuels in treated and untreated ponderosa pine forests of the southern Rocky Mountains. Int J Wildl Fire. https://doi.org/http://dx.doi.org/10.1071/WF16072