Comparing Methods for Estimating Woody Debris Properties in a Mixed-Conifer Forest

Natalie A. Coy

ABSTRACT

Due to historical fire suppression, forests managers have to deal with high accumulations of wildland fuel loads. The use of prescribed fires to reduce these fuel loads requires explicit information on fuel characteristics and weight. Land managers frequently use species-specific squared quadratic mean diameters (QMD^2) calculated by van Wagtendonk et al. (1996) to estimate regional fine woody debris (FWD) diameters. However, the van Wagtendonk et al. (1996) study took place in single species tree stands and has not been validated in a mixed-conifer forest in the Sierra Nevada. Data for this study was collected in the summer of 2020 at Blodgett Forest Research Station in California. Of the three timelag classes (1-hour, 10-hour, 100-hour), only 1-hour fuels had a significant relationship between measured and estimated QMD^2. Additionally, this study found that the van Wagtendonk et al. (1996) approach outperforms both a linear model and a generalized linear model. These findings demonstrate that the estimated FWD diameters remained within a likely range for all three timelag classes and therefore using the van Wagtendonk et al. (1996) QMD^2 values is a valid approach. This information is crucial to land managers as this approach will continue to save time and resources while providing the information needed to implement fuel treatments.

KEYWORDS

Fire, forest management, Sierra Nevada, fuel loads, prescribed fires

INTRODUCTION

Western United States forests have massive wildland fuel build up and dense forest structures due to the suppression of naturally occurring wildfires, historic timber harvesting practices, and livestock grazing patterns (Stephens et al. 2004, Keeley and Syphard 2019). These forest ecosystems are vulnerable to high intensity fires as increased fuel loads and dense forest stands allow fires to burn at higher temperatures (Keeley and Syphard 2019). Moreover, fire risk is increasing as changing climate conditions have led to increases in average air temperatures and longer fire seasons (Keeley and Syphard 2019). Of the three key factors which influence wildfire behavior – topography, weather, and fuels – wildland fuels is the only parameter which humans can control and manage (Belongie and Minnich 2018, Rollins 2004).

To effectively manage fuel loads, forest managers must understand the characteristics of the fuel they are targeting. Fuel type (surface, ladder, or crown), fuel quantity, and the size of the fuels are key features that define how fuels behave in fire (Stephens et al. 2018b). Further, as varying fuels respond differently to management techniques, fire managers must have explicit information on fuel characteristics in order to implement effective fuel treatments (Agee et al. 2000, Keeley and Syphard 2019). For example, a build up of surface fuels (shrubs, grasses, saplings and plant debris) can lead to spatial continuity along the forest floor, allowing fires to build in momentum and increase their fire intensity (Miller and Urban 2000). An effective technique to manage surface fuels is prescribed burns as these low intensity fires will break up the continuity of fuels and decrease overall fuel quantity (North et al. 2009). However, prior to implementing a prescribed burn, managers must calculate fuel loading to predict fire behavior and safely accomplish the burn (van Wagtendonk et al. 1996).

Researchers have developed protocols to obtain information on the physical properties of fuels. The Brown (1974) *Handbook for inventorying downed woody material* is a widely used and referenced protocol for estimating fuel loads. Brown's protocol uses a planar intersect technique to group fine woody debris (FWD) into size classes that are based on fuel moisture timelag classes: 1-hour (< 0.6 cm diameters), 10-hour [0.6 - 2.5 cm diameters), 100-hour [2.5 - 8 cm diameters), and 1000 hour fuels [> 8 cm) (Brown 1974). A timelag class refers to the time a fuel particle requires in order to reach 63% of its equilibrium moisture content (van Wagtendonk et al. 1996).

Fuel load information can then be used to inform fire models, such as the Rothermel (1972) fire spread model which accounts for differences in fuel load sizes and weather conditions to estimate fire behavior (van Wagtendonk et al. 1996). Therefore, the more accurate information on fuel load characteristics, the more accurate fire models can be at predicting fire behavior (Heinsch et al. 2010). However, measuring each individual FWD diameter within a fuel load is labor and time-intensive for researchers.

In order to remedy this, van Wagtendonk et al. (1996) calculated squared quadratic mean diameters (QMD^2) for 19 of the 22 conifers present in the Sierra Nevada region. Specifically, the study went into single species tree stands in Yosemite National Park and measured diameters for each tree species (van Wagtendonk et al. 1996). Today, researchers use van Wagtendonk et al. (1996) QMD^2 with their measured forest composition in order to estimate expected FWD QMD^2 (e.g., Saah et al. 2016, Knapp et al. 2017, Cansler et al. 2019). Although van Wagtendonk et al. (1996) QMD^2 are being used by forest managers, they have never been tested for accuracy and precision in a mixed-conifer forest.

The goal for this study is to determine whether using van Wagtendonk et al. (1996) approach can estimate an accurate and precise representation of measured FWD diameters in a mixed-conifer forest in the Sierra Nevada. To address this, this study collected data on forest composition as well as the measured FWD QMD^2. Further, this study uses the van Wagtendonk et al. (1996) approach to calculate estimated FWD QMD^2 and compares these results against the empirical data. Lastly, this study explores two other predictive models, a linear model and a generalized linear model (GLM), to see whether there is a more accurate approach for estimating FWD QMD^2 in a mixed-conifer forest.

METHODS

Study site

This study took place at the University of California Blodgett Forest Research Station (Blodgett Forest, 38°54’45”N, 120°39’27”W). Blodgett Forest is located east of Georgetown, CA (approx. 100 km northeast of Sacramento, Figure 1) and is a mixed-conifer forest in the north-central zone of the Sierra Nevada. This area encompasses 1763 ha and is between 1200 and 1500 m above sea level (Stephens et al. 2012). The tree species found in this forest include: ponderosa pine *(Pinus ponderosa*), sugar pine (*Pinus lambertiana*)*,* white fir (*Abies concolor*)*,* incense-cedar (*Calocedrus decurrens*), douglas-fir (*Pseudotsuga menziesii*)*,* giant redwood *(Sequoiadendron giganteum*)*,* California black oak (*Quercus kelloggii*)*,* tanoak (*Notholithocarpus densiflorus*)*,* bush chinquapin (*Chrysolepis sempervirens*)*,* Pacific madrone *(Arbutus menziesii*) and Giant chinquapin *(Chrysolepis chrysophylla*).

Figure 1. Map of California and Blodgett Forest Research Station. Blodgett Forest Research Station pointed out with a red dot and black arrow. Image derived from *Yoshioka et al. 2017*

Blodgett Forest experiences a Mediterranean climate with summer months having a predictable dry period that extends into the fall. Weather data reports, recorded daily since 1961, show most of the precipitation occurs during winter and spring months and averages 166 cm per year (Stephens and Collins 2004). Summer temperatures typically range from 14°C to 27°C, while winter temperatures range from 0°C to 9°C (Stephens and Collins 2004). Prior to recent fire suppression efforts in the nineteenth century, Blodgett Forest had a natural disturbance regime of low-severity fires with a mean return interval of 13 years (Stephens and Collins 2004). After the site was established as a research forest in 1931, the University of California, Berkeley began active management in the mid-1950s (Regents of the University of California 2020). The research forest is broken up into numerous compartments where researchers at UC Berkeley conduct different management approaches.

In this study the data was collected in three compartments at Blodgett Forest (Figure 2) that have only received single tree selection management (Olson and Helms 1996). These compartments are relatively similar to one another in terms of topography and size. The total size of our study site is 23 ha; with Compartment A being 8.9 ha, Compartment B being 7.5 ha, and Compartment C being 6.6 ha. Within each compartment are plot markers used as the plot centers for the transets.

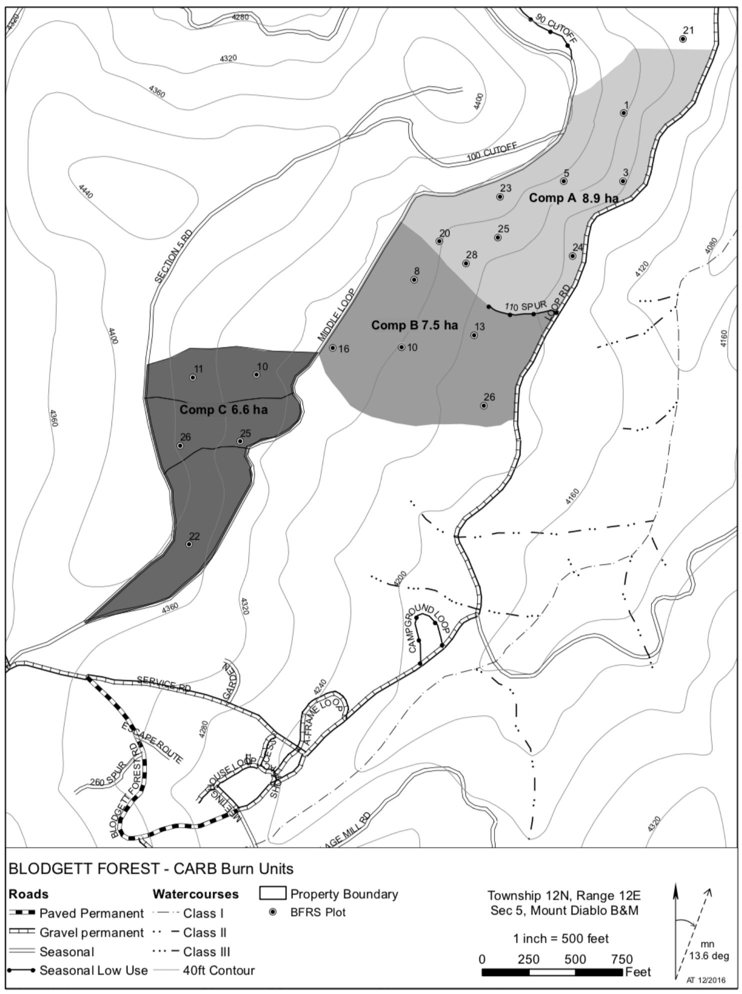

Figure 2. Map of Blodgett Forest. The study site compartments highlighted and labeled as Comp A, B and C. Each compartment size is included (A = 8.9 ha, B = 7.5 ha, C = 6.6 ha) and the number markers represent the location of our 18 plot centers. (Figure from Foster pers. communication)

Defining fuel components and SENT protocol

The Spatially Explicit Nested Transects (SENT) protocol was designed by Daniel Foster at UC Berkeley (Daniel Foster pers. communication) and the data collection was completed by field technicians during the summer of 2020 at Blodgett Forest Research Station.

Specifically, this study focuses on three timelag classes of fine woody debris (FWD) diameters. These timelag classes include 1-hour (< 0.6 cm diameters), 10-hour [0.6 - 2.5 cm diameters), and 100-hour [2.5 - 8 cm diameters) fuels. To measure these fuel components field technicians used the SENT protocol which is based on the Brown's (1974) protocol but has modifications to provide information on the spatial patterns of fuels. While the SENT protocol collects information on all fuel categories, only the data collected for FWD and trees was used for this study.

Within the study area, SENT samples were placed on 18 pre-existing plot centers. These plot centers were chosen by the researcher of the forest station and took into account that the area was homogeneous with respect to vegetation and topography as well as maintained a flat topography with less than 10 percent slope to minimize the influence on woody fuel alignment. For every SENT sample there were four 30m transects that ran outward in cardinal directions from the plot center. Transects measurements were cut off if the transect extended beyond the compartment border. The tree and snags measurements were recorded within 5m wide by 15m long belt transects starting from plot center and radiating out at cardinal directions. The measurements for FWD diameters were sampled between 19 - 20m on the transect.

Data collection

Inventory was taken for all trees and snags that had a diameter at breast height (DBH) that was greater than or equal to 11.43cm. Any trees that were forked below breast height were counted as two trees (Brown 1974). The data collected for trees and snags included the status of the tree (dead or living), species name, DBH to the nearest 0.1 cm, height to the nearest 0.1m from the uphill side, and any observation comments (Brown 1974). For every piece of FWD that intersected the transect between 19 - 20m, diameter measurements (0-7.62cm) were taken. To measure particles as FWD it had to be detached from the original source of growth and their central axis was above the duff layer (Brown 1974). The diameter measurements were taken to the nearest mm where the piece of FWD intersected the transect.

Data analysis

To understand the forest composition of each plot (plot size is 500 m^2 or 0.05 of a hectare), the percentage of basal area (pBA) and tree species prevalence were calculated. Basal area (m^2 per hectare) refers to the sum of cross-sectional surface areas of live trees within a stand (Bettinger et al. 2017). Prior to any calculations, observed tree species were compared to tree species present in van Wagtendonk's study, grouping any trees that were present on our site but not in van Wagtendonk into an *Other* category. Additionally, any trees that had a diameter less than 11.4 cm were excluded. Tree diameters were measured at diameter breast height (DBH) or approximately 4.5 ft above the ground and basal area was calculated from the formula:

$$\text{Basal area} = \pi \left(\frac{DBH^2}{4}\right)$$

To obtain the pBA per plot, the basal area for each tree species was first summed then divided by the total sum of basal area for all trees within that plot. pBA was then used to understand the prevalence of each tree species at the plot level.

To compare measured FWD diameters to estimated FWD diameters, the study calculated squared quadratic mean diameters (QMD^2) for both variables. Measured QMD^2 was calculated by squaring each particle's diameter and taking the average of the sum for each plot and size class:

$$QMD^2 = \frac{\Sigma d^2}{n}$$

where QMD^2 is the squared quadratic mean diameter, *d* is the diameter, and *n* is the number of particles. QMD^2 was calculated at the plot level as this was the resolution of our tree data. To determine the estimated FWD QMD^2, I used QMD^2 values from van Wagtendonk (1996) study and multiplied this by the calculated prevalence of tree species at each plot. To compare these two variables, statistical analyses were performed to understand overall fuel variability for each size class. Additionally, a Pearson's correlation test was run to determine the linear relationship of the two variables. All significance tests were at the 0.05 level.

To determine the best approach for estimating FWD QMD^2 from the prevalence of surrounding tree species, this study used the measured FWD diameter data to create two predictive models, one linear regression model and one generalized linear model (GLM), to compare with the van Wagtendonk et al. (1996) approach. The linear regression model follows the formula:

$$Y_i = \alpha + \beta \times X_i + \varepsilon_i \text{ where } \varepsilon_i \sim N(0, \sigma^2)$$

where Y_i was the response variable, measured FWD QMD^2, X_i were the explanatory variables, which included the pBA for each tree species, ε_i was the residuals, α and β were the intercept and slope, and the model was assumed to be normally distributed with expectation 0 and variance σ^2 (Zuur 2009). The GLM consists of three components: a random component, a linear predictor, and a link function (Fox 2015). This study used a GLM with gamma distribution and a log link function. Gamma distributions are a continuous family with probability-density function indexed by the scale parameter $\omega > 0$ and shape parameter $\psi > 0$ (Fox 2015). The GLM equation follows the formula:

$$g(\log_e \mu_i) = \eta_i = \alpha + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_k X_{ik}$$

where X_{ij} were prespecified functions of the explanatory variables, in this study they were the pBA of each tree species, $g(\log_e \mu_i)$ was the log link function that transforms the expectation of the response variable, $\mu_i \equiv E(Y_i)$, to the linear predictor η_i (Fox 2015). This model used a log link which represents an underlying multiplicate process that is common in ecology. To compare these two models with the van Wagtendonk approach, I calculated R^2 values for each model then performed a leave-one-out cross validation (LOO-CV) analysis where I calculated Mean Absolute Error (MAE) and Percent Bias (PB) as my measurements of predictive accuracy. MAE was used to determine the precision of the models while PB was used to determine the accuracy of them.

Cross-validation (CV) was used to test for the accuracy and precision of the predictive equations by splitting the data into parts that were used to: (1) train the model and (2) test the model (Burkner et al. 2020). In a LOO-CV, every observation is used as a validation set (Burkner et al. 2020). All statistical analysis was done in R statistical computing software.

RESULTS

Forest Composition

The forest composition of the study site included six van Wagtendonk tree species: white fir (ABCO), incense-cedar (CADE), sugar pine (PILA), ponderosa pine (PIPO), Douglas-fir (PSME), and giant redwood (SEGI). Additionally, the site contained three *Other* tree species: California black oak (QUKE), tanoak (NODE), and giant chinquapin (CHCH). Tree species Pacific madrone (ARME) and Pacific dogwood (CONU) were also found on the site, however none of these trees had diameters larger than 11.4 cm so they were excluded from the analysis.

Forests varied in composition but most were generally dominated by ABCO, CADE, and PSME (Figure 1). However, plots A-001, A-025, and B-010 had no presence of PIPO (Figure 1). Plots B-008 and B-010 had a higher proportion PILA compared to the other plots. At the compartment level, CADE had the highest prevalence for all three compartments followed by ABCO, PSME, and PIPO (Table 1). Overall the three compartments are relatively similar in forest composition, however vary slightly in total basal area. For example, Compartment A had a total basal area of 1658.07 m^2/ha with a plot mean of 207.26 m^2/ha (sd = 52.84), while Compartment B had a total basal area of 894.19 m^2/ha with a plot mean of 178.84 m^2/ha (sd = 33.12), and Compartment C had a total basal area of 1275.68 m^2/ha with a plot mean of 255.14 m^2/ha (sd = 61.97).

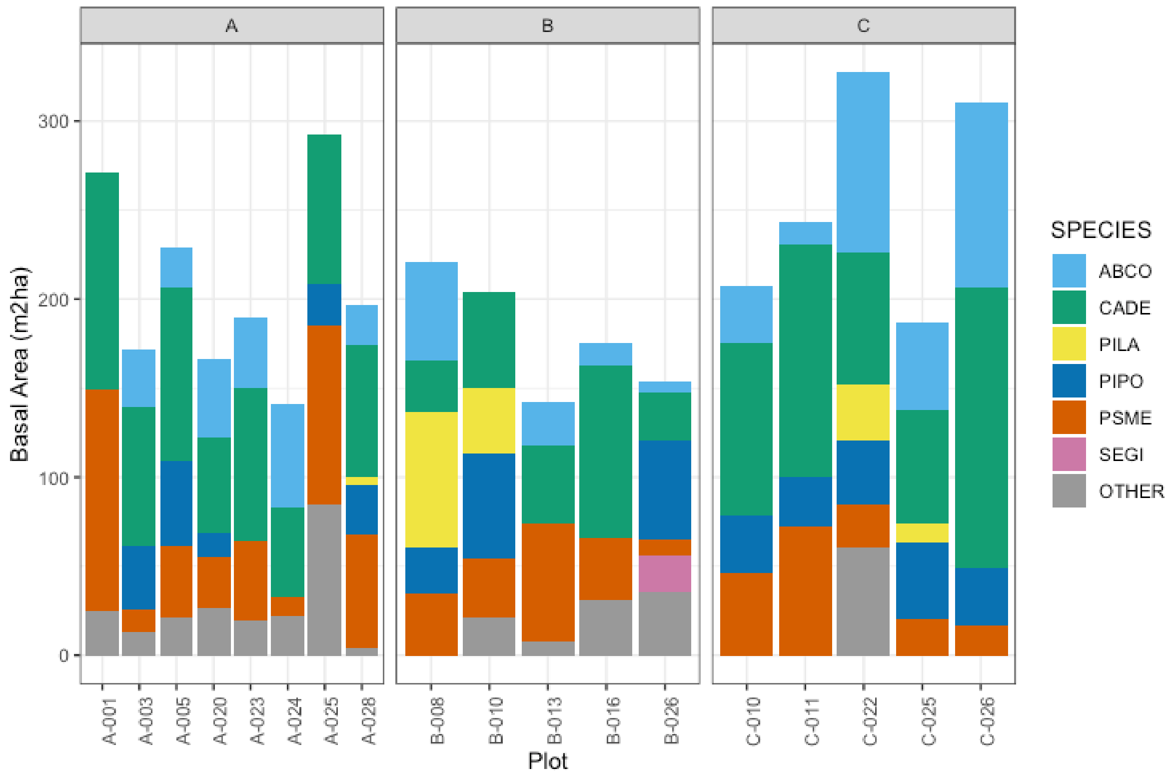

Figure 3. Prevalence of tree species. The overall percentage of each tree species for each plot. Tree species: white fir (ABCO), incense-cedar (CADE), sugar pine (PILA), Ponderosa pine (PIPO), douglas-fir (PSME), giant redwood (SEGI) and Other (California black oak, tanoak, and giant chinquapin).

Table 1. Species prevalence per compartment. Values are representative of each species relative proportion of total basal area at the compartment level. Tree species: white fir (ABCO), incense-cedar (CADE), sugar pine (PILA), Ponderosa pine (PIPO), douglas-fir (PSME), giant redwood (SEGI) and Other (California black oak, tanoak, and giant chinquapin).

COMP	ABCO	CADE	PILA	PIPO	PSME	SEGI	OTHER
A	0.159	0.392	0.00286	0.0895	0.233	0.0000	0.1230
B	0.106	0.285	0.10500	0.1540	0.210	0.0275	0.1130
C	0.223	0.416	0.03010	0.1430	0.151	0.0000	0.0372

Measured QMD² compared to van Wagtendonk estimated QMD²

For 1-hour fuels, the measured mean QMD² was 0.105 cm² (sd = 0.025) and the van Wagtendonk estimated mean was 0.104 cm² (sd =0.019). For 10-hour fuels, the measured mean was 1.618 cm² (sd = 0.362) and the van Wagtendonk estimated mean was 1.328 (sd = 0.035). For 100-hour fuels, the measured mean was 15.347 cm² (sd = 8.702) and the van Wagtenodnk estimated mean was 16.422 cm² (sd = 0.997). For 1-hour fuels, measured and estimated QMD² were correlated (p-value = 0.019) with a correlation coefficient of 0.547 and a 95% confidence interval of [0.108, 0.808]. For 10-hour fuels, the relationship was not significant (p-value = 0.120) with a correlation coefficient of -0.380 and a 95% confidence interval of [-0.719, 0.105]. The relationship was also not significant for 100 hour fuels (p-value = 0.833) with a correlation coefficient of 0.0535 and a 95% confidence interval of [-0.424, and 0.508]. The only significant linear relationship between measured and van Wagtendonk estimated QMD² was for 1-hour fuels (Figure 4). There was no significant linear relationship between measured and estimated QMD² for 10-hour and 100-hour fuels.

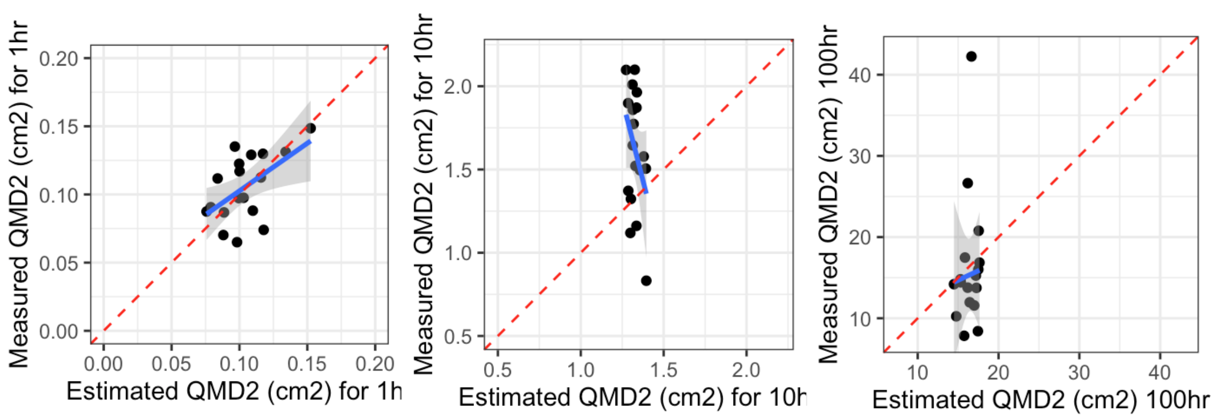

Figure 4. Linear regressions of measured and estimated squared quadratic mean diameter (QMD²) . The blue line represents the linear regression model for each time-lag class and the red dashed line represents a perfect fit between the measured and the estimated QMD².

Linear modeling and GLM

For 1-hour fuels, the linear model estimated mean was 0.114 cm² (sd = 0.028) and the GLM estimated mean was 0.1138 cm² (sd = 0.027). For 10-hour fuels, the linear model estimated mean was 1.569 cm^2 (sd = 0.283) and the GLM estimated mean was 1.571 cm^2 (sd = 0.292). For 100-hour fuels, the linear model estimated mean was 16.330 cm^2 (sd = 2.813) and the GLM estimated mean was 16.403 cm^2 (sd = 2.840).

For all three timelag classes, I found that the van Wagtendonk approach estimated the most accurate and precise QMD^2 values compared to the linear model and the GLM (Figure 5). For instance, the van Wagtendonk approach had higher R^2 values for each fuel class (1-hour: 0.363; 10-hour: 0.0801; 100-hour: 0.660) whereas the GLM model had lower R^2 values (1-hour: 0.0175; 10-hour: 0.0309; 100-hour: 0.376) and the linear model had the lowest R^2 values (1-hour: 0.00855; 10-hour: 0.0268; 100-hour: 0.00573) (Table 2). Additionally, the van Wagtendonk approach had MAE values for 1-hour and 100-hour fuels that were closer to zero compared to the GLM and linear model (Table 2). Moreover, the van Wagtendonk approach had PB values for 1-hour and 10-hour fuels that were closer to zero compared to the GLM and linear model (Table 2). Although the van Wagtendonk 10-hour and 100-hour fuels had either MAE or PB values further from zero, accordingly, the overall comparison of these three timelag classes indicate that the van Wagtendonk approach outperforms the other two models (Table 2).

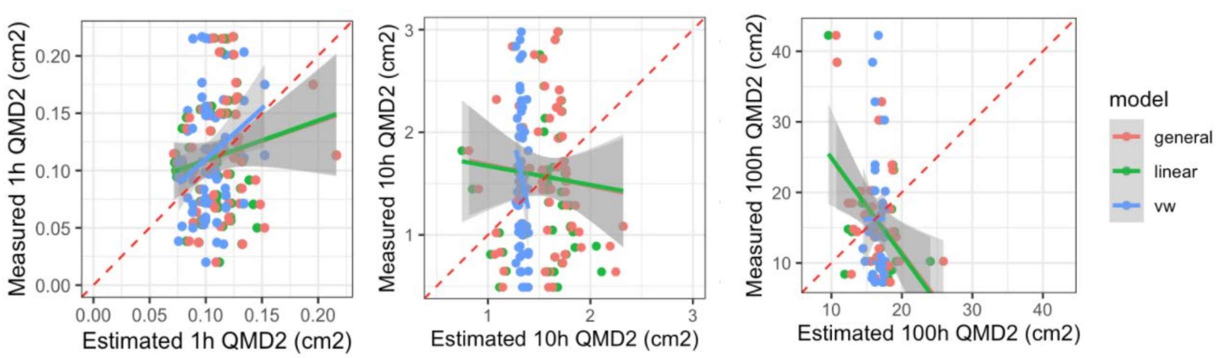

Figure 5. Measured and estimated squared quadratic mean diameter (QMD^2). Values for the van Wagtendonk approach (blue), linear model (green) and generalized linear model (orange). Red dashed lines represent a perfect fit between the measured and the estimated QMD^2.

Table 2. Leave-one-out cross-validation. Comparison of the van Wagtendonk approach (vm), linear model (lm), and generalized linear model (glm) across fuel timelag classes. Statistics of R^2 values, mean absolute error (MAE), and percent bias (PB). For all three timelag classes, the van Wagtendonk approach has the highest R^2 value and for 1-hour and 100-hour van Wagtendonk has the lowest MAE as well as the lowest PB for 1-hour and 10-hour fuels.

	R^2			MAE			PB		
timelag_class	**lm_r2**	**vw_r2**	**glm_r2**	**lm_mae**	**vw_mae**	**glm_mae**	**lm_pb**	**vw_pb**	**glm_pb**
1 hr	0.00855	0.3630	0.0175	0.0483	0.0421	0.0478	-0.413	-0.2630	-0.408
10 hr	0.02680	0.0801	0.0309	0.5120	0.5230	0.5100	-0.121	-0.0102	-0.117
100 hr	0.00573	0.6600	0.0376	6.3100	5.0000	6.3800	0.103	0.1160	0.108

DISCUSSION

Understanding potential fire behavior is essential for implementing prescribed burns and requires explicit information on fuel characteristics such as fine woody debris (FWD) diameter measurements (Agee et al 2000). However, measurements of FWD diameters are time intensive and hence typically infeasible for many researchers. Therefore, the van Wagtendonk et al. (1996) study wanted to quantify the physical fuel properties of 19 of the Sierra Nevada conifers so that managers could use the best available data to assure accurate and precise fuel load estimates. The results of this paper suggest that while the van Wagtendonk FWD QMD^2 estimates had no linear significance to the measured QMD^2, the estimates had similar means and standard deviations as the empirically measured fuels and therefore validates using this approach. Additionally, this study found that the van Wagtendonk approach outperforms both a linear model and a generalized linear model.

Forest composition of Blodgett Research Station

The forest composition of the three compartments studied at Blodgett Forest were dominated by incense-cedar, Douglas-fir, and white-fir. These findings support Olson and Helms (1996) study where they investigated four forest wide inventories (1934, 1946, 1955, 1973) and found that sugar pine and ponderosa pine were declining over the years and incense-cedar and

Douglas-fir were increasing. This shift in dominant vegetation has been attributed to the change in local fire regime from frequent, low-intensity fires to fire suppression (Eitzel et al. 2015). Moreover, the different survival mechanisms of more shade tolerant species – incense-cedar, Douglas-fir, and white-fir – in the understory has led to their success (Olson and Helms 1996, Eitzel et al. 2015). Ponderosa pine and sugar pine are shade-intolerant and rely on disturbance to recruit in forest gaps (Eitzel et al. 2015). Additionally, this study found a limited number of giant sequoia, California black oak, tanoak and giant chinquapin. This finding supports the Eitzel et al. (2015) study which found that within Blodgett Forest these species account for only 9.5% of the forest. Understanding the forest composition at Blodgett Forest Research Station is essential for managers to estimate fuel weight as different species have characteristics causing them to burn differently.

Relationship of measured to van Wagtendonk estimates of FWD diameters

Of the three fuel timelag classes, only 1-hour fuels were correlated to van Wagtendonk's estimated values. This is supported by the findings on overall fuel variability where measured and estimated FWD QMD^2 for 1-hour fuels have nearly identical mean values with only a slightly larger standard deviation for measured values. Meanwhile, for 10-hour and 100-hour fuels the mean values were close in range, but standard deviations for measured values were much higher than estimated. This result shows that measured FWD QMD^2 values fluctuate more around the mean than was being predicted by van Wagtendonk's approach. Further, my findings suggest that 10-hour fuels are being underestimated and 100-hour fuels are being overestimated.

The purpose of van Wagtendonk et al. (1996) study was to measure fuel properties in the Sierra Nevada as they could vary significantly by region of the country and land managers were currently using measurements from studies that took place in the Rocky Mountains (Brown and Roussopoulos 1974, Ryan and Pickford 1978). van Wagtendonk et al. (1996) compared their results with these two other studies and found slight differences in squared quadratic mean diameters across size classes and species. From these findings, van Wagtendonk et al. (1996) suggested that if managers in the Sierra Nevada used values from Brown and Roussopoulos (1974) for fuel weight estimates it would result in overestimations and underestimations. These findings are similar to my findings, where the van Wagtendonk et al. (1996) approach slightly underestimates 1-hour fuels, underestimates 10-hour fuels, and overestimates 100-hour fuels. This is likely due to the fact that while the van Wagtendonk et al. (1996) study took place in the Sierra Nevada, it took all of its measurements in single species stands whereas my study was in a mixed-conifer forest. Although the van Wagtendonk et al. (1996) approach did not produce linear correlations for the 10-hour and 100-hour fuels, the estimates produced similar means and standard deviations for all three timelag classes. My findings support using the van Wagtendonk et al. (1996) approach for estimating FWD diameters in a mixed-conifer forest in the Sierra Nevada.

Modeling FWD diameters

The van Wagtendonk et al. (1996) approach for estimating FWD diameters outperforms both the linear model and generalized linear model for all three fuel timelag classes (1-hour, 10-hour, 100-hour). Through my leave-one-out cross validation test, I found that the van Wagtendonk et al. (1996) approach produced R^2 values that were closer to 1, as well as mean absolute error (MAE) values and percent bias (PB) values that were closer to 0 when compared against the other two models. Additionally, I found that all three models underestimated the 1-hour and 10-hour fuels, and overestimated the 100-hour fuels. My results suggest that forest managers and researchers should continue using van Wagtendonk's QMD^2 to calculate fuel weight in mixed-conifer forests in the Sierra Nevada. My study validates the methodology of previous studies such as Saah et al. (2016), Knapp et al. (2017), and Cansler et al. (2019) that have used van Wagtendonk et al. (1996) coefficients and equations to calculate fuel weights.

Synthesis

Forest researchers should continue to use the van Wagtendonk et al. (1996) approach when estimating fine woody debris diameters in mixed-conifer forests in the Sierra Nevada. These findings demonstrate that the estimated FWD diameters remained within a likely range for all three timelag classes. This information is crucial to land managers as by being able to use the van Wagtendonk et al. (1996) approach will continue to save time and resources. Additionally, it allows managers to accurately predict potential fire behavior so that they are able to plan and implement effective prescribed burns that accomplish management goals.

Limitations and Future Directions

This study had taken tree data at the plot level, so to avoid pseudoreplication all of our data was aggregated up to the plot level prior to calculating FWD QMD^2. This shrunk our data size down to 18 points which made it difficult to create an accurate and precise predictive model. Therefore, future studies that aim to improve the approach for estimating FWD diameters study should have a large data set. This is crucial as predictive models require the data to be split into training and testing groups. Additionally, to validate models it is important that they are tested on outsourced or unused data to ensure generalizability.

Broader Implications

Fuel loads play an important role in the Rothermel (1972) fire spread equation and therefore having an accurate estimation of fine woody debris diameters is essential for effective fuel management (van Wagtendonk et al. 1996). Additionally, fire risk will continue to increase as changing climate conditions will affect weather patterns and fire season durations (Westerling et al. 2011). The demand for cost efficient fire management will be necessary in order to mitigate the effects of high fuel loads and our history of fire suppression to protect not only surrounding wildlife as well as human life and property.

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REFERENCES

Agee, J.K., B. Bahro, M. A. Finney, P. N. Omi, D. B. Sapsis, C. N. Skinner, J.W. van Wagtendonk, and C. P. Weatherspoon. 2000. The use of shaded fuel breaks in landscape fire management. Forest Ecology and Management 127: 55–66.

Belongie, B. L., and R. A. Minnich. 2018. Fire Weather Principles. *Fire in California's Ecosystems*: 27-38.

Brown, J.K. 1974. Handbook for inventorying downed woody material. Gen. Tech. Rep. INT-16. Ogden, UT: U.S. Department of Agriculture, Forest Service, Intermountain Forest Range and Range Experiment Station. 24 p.

Brown, J.K. and P. J. Roussopoulos. 1974. Eliminating biases in the planar intersect method for estimating volumes of small fuels. Forest Science 20(4): 350 - 356.

Burkner, P., J. Gabry, and A. Vehtari. 2020. Efficient leave-one-out cross-validation for Bayesian
non-factorized normal and Student-t models. Computational Statistics: https://doi.org/10.1007/s00180-020-01045-4

Cansler, C. A., M. E. Swanson, T. J. Furniss, and J.A. Lutz. 2019. Fuel dynamics after reintroduced fire in an old-growth Sierra Nevada mixed-conifer forest. Fire Ecology 15(1): DOI:10.1186/s42408-019-0035-y

Fox, J. 2015. Generalized linear models. Pages 379-424 *in* J. Fox, editor. Applied Regression Analysis and Generalized Linear Models. SAGE Publications, McMaster University, Canada.

Heinsch, F. A., P. L Andrews, and L. Patricia. 2010. BehavePlus fire modeling system, version 5.0: Design and Features. Gen. Tech. Rep. RMRS-GTR-249. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 111 p.

Keeley, J. E. and A. D. Syphard. 2019. Twenty-first century California, USA, wildfires: fuel-dominated vs wind-dominated fires. Fire Ecology 15.

Knapp, E., J. M. Lydersen, M. P. North, and B. M. Collins. 2017. Efficacy of variable density thinning and prescribed fire for restoring forest heterogeneity to mixed-conifer forest in the central Sierra Nevada, CA. Forest Ecology Management 406: 228 - 241.

Miller, C., and D. L. Urban. 2000. *Connectivity of forest fuels and surface fire regimes*. Page *Landscape Ecology*.

North, M., P. Stine, K. O'Hara, W. Zielinski, and S. Stephens. 2009. An ecosystem management strategy for Sierran mixed-conifer forests. Gen. Tech. Rep. PSW-GTR-220. Albany, CA: U.S. Department of Agriculture, Forest Service, Pacific Southwest Research Station. 49 p.

Rollins, M. G., R. E. Keane, and R. A. Parsons. 2004. Mapping fuels and fire regimes using remote sensing, ecosystem simulation, and gradient modeling. Ecological Applications 14 (1): 75 - 95.

Rothermel, R. C. 1972. A mathematical model for fire spread predictions in wildland fuels. United States Department of Agriculture, Forest Service, Research Paper INT-116. Intermountain Forest and Range Experiment Station, Ogden, Utah 40 pages.

Ryan, K. C. and S. G. Pickford. 1978. Physical properties of woody fuels in the Blue Mountains of Oregon and Washington. United States Department of Agriculture, Forest Service, Research Note PNW-315. Pacific Northwest Forest and Range Experiment Station, Portland, Oregon. 10 pages.

Saah, D., D. Schmidt, G. Roller, T. J. Moody, J. Moghaddas, and T. Freed. 2016. Consultant report carbon storage and mass balances: characteristics of forest carbon and the relationship between fire severity and emissions in the Sierra Nevada, California, USA. Prepared for: California Energy Commission.

Stephens, S. L., and B. M. Collin. 2004. Fire regimes of mixed conifer forest in the north-central Sierra Nevada at multiple spatial scales. Northeast Science 78: 12-23.

Stephens, S. L., B. M. Collins, C. J. Fettig, M. A. Finney, C. M. Hoffman, E. E. Knapp, M. P. North, H. Safford, and R. B. Wayman. 2018a. Drought, tree mortality, and wildfire in forest adapted to frequent fire. BioScience 68(2): 77-88.

Stephens, S. L., S. J. Husari, H. T. Nichols, N. G. Sugihara, and B. M. Collins. 2018b. Fire and Fuel Management. *Fire in California's Ecosystems*: 411-428.

Stephens, S. L., B. M. Collins, and G. Roller. 2012. Fuel treatment longevity in Sierra Nevada mixed conifer forest. Forest Ecology and Management 285: 204-212.

van Wagtendonk, J., J. M. Benedict, and W. M. Sydoriak. 1996. Physical properties of woody fuel particles of Sierra Nevada conifers. International Journal of Wildland Fire 6(3): 117-123.

Westerling, A.L., B.P. Bryant, H.K. Preisler, T.P. Holmes, H.G. Hildalgo, T. Das, and S.R.

Shrestha. 2011. Climate change and growth scenarios for California wildfire. Climatic Change 109: 445-463.

Yoshioka, T. R. Sakurai, S. Kameyama, K. Inoue, and B. Hartsough. 2017. The optimum slash pile size for grinding operations: grapple excavator and horizontal grinder operations model based on a Sierra Nevada, California survey. Forest 8 (11): 442.