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Bayesian Techniques for Surface Fuel Loading Estimation

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Abstract

Abstract—*A study by Keane and Gray (2013) compared three sampling techniques for estimating surface fine woody fuels. Known amounts of fine woody fuel were distributed on a parking lot, and researchers estimated the loadings using different sampling techniques. An important result was that precise estimates of biomass required intensive sampling for both the planar intercept and fixed-area plot methods. This study explores Bayesian statistical methods as a means to reduce the sampling effort needed to obtain a desired precision. We found that Bayesian techniques dramatically increased the precision compared to using no prior information from the site.*

Keywords: Bayesian, precision, fuel loading, fixed-area plot, planar intercept

Gray, Kathy; Keane, Robert; Karpisz, Ryan; Pedersen, Alyssa; Brown, Rick; Russell, Taylor. 2016. **Bayesian techniques for surface fuel loading estimation.** Res. Note RMRS-RN-74. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 9 p.

Forest Service | **Rocky Mountain Research Station** | Research Note RMRS-RN-74 | September 2016

INTRODUCTION

Fuel loadings are important inputs for calculating fuel consumption (Reinhardt and Holsinger 2010), smoke emissions (Hardy et al. 2000; Ottmar 1983), soil heating (Campbell et al. 1995), carbon stocks (Reinhardt and Holsinger 2010), wildlife habitat (Bate et al. 2004), and site productivity (Brais et al. 2005; Hagan and Grove 1999). Additionally, fuel biomass can be directly manipulated to restore ecosystems, lower fire intensity, minimize plant mortality, and reduce erosion (Graham et al. 2004; Ingalsbee 2005; Reinhardt et al. 2008). Accurate estimates of fuel loadings are needed for nearly every phase of fire management including fighting wildfires (Chen et al. 2006; Ohlson et al. 2006), implementing prescribed burns (Agee and Skinner 2005), describing fire danger (Deeming et al. 1977; Hessburg et al. 2007), and predicting fire effects (Ottmar et al. 1993; Reinhardt and Keane 1998).

Keane and Gray (2013) compared three sampling techniques for estimating fine woody debris (FWD). Their study entailed creating fuelbeds of four known woody fuel loadings (0.05, 0.10, 0.15, and 0.20 kg m^{-2}) and distributing these fuels in three different spatial patterns (uniform, patchy, and jackpot) in the parking lot of the Missoula Fire Science Laboratory, Montana, USA. Trained technicians estimated loadings for the fine woody fuels (diameter <8 cm) using the photoload (Keane and Dickinson 2007), planar intercept (Brown 1974), and fixed-area plot methods (Keane et al. 2012). The photoload method uses calibrated photos of known loadings pointing toward the forest floor to visually estimate fuel loadings (Keane and Dickinson 2007). It is the most recently developed method and the simplest to implement; however, it relies heavily on proper training and is consequently subject to human error. To execute the fixed-area plot method, a 1-m-square plot was used to define a sample frame with a fixed area. The dimensions (length, diameter) of all fuels within the plot boundary were measured to calculate volume, which was then multiplied by field-estimated particle densities to estimate fuel loadings (Keane et al. 2012). The fixed-area plots required a significant investment of time and money (Keane and Gray 2013). Finally, the planar intercept method uses vertical sampling planes that are placed across the plot of interest. Diameters of the twigs that intersect the plane are measured and used to compute fuel load. The planar intercept method has been used extensively in many fuel inventory and monitoring programs because it is relatively fast and simple to use (Busing et al. 2000; Lutes et al. 2006; Waddell 2001).

These three methods, and multiple variants of their computational algorithms, were then compared to determine which method was the most accurate and precise in estimating fine woody fuels. In summary, Keane and Gray (2013) found that the photoload method is the quickest method but the least accurate, underestimating FWD for almost all but the lightest loading (0.05 kg m^{-2}). Although the photoload method performed poorly here, it performed better in a study done by Sikkink and Keane (2008). Keane and Gray (2013) suggested that the poor performance of the photoload method might be due to the technicians' limited expertise. Although the fixed-area and planar intercept methods were more accurate than the photoload method, they were also more labor-intensive. The authors noted that to obtain accurate planar intercept measurements one should use at least 400 m of transect to reduce variability to within 20 percent of the mean (Keane and Gray 2013).

A method not examined in Keane and Gray's study was the photo series method. This method, initially developed by Maxwell and Ward (1976), is a technique that uses photos with known fuel loadings to estimate FWD (Sikkink and Keane 2008). The National Fuels Photo Series can be used to describe surface fuels including shrub, forb, and grass biomass (Sikkink and Keane 2008). The photo series method would have been an appropriate technique to apply in Keane and Gray's (2013) study.

The study design of Keane and Gray (2013) provides a nice platform to study the use of Bayesian methods to estimate FWD. Bayesian methods differ from frequentist statistics (those used in Keane and Gray [2013]) in that Bayesian methods incorporate prior information to predict fuel loadings. This prior information can be expert opinion or information gathered from a previous study. For our purposes, we will assume that the prior information would be obtained from visual methods of estimating FWD such as the photoload or photo series methods. Wright and colleagues (2010) state that two photos from the photo series may be used to estimate loadings. Two photos from the photo series or photoload technique could estimate the minimum and maximum fuel loading at a site and could then be treated as prior information when either the planar intercept or fixed-area method is used to estimate FWD.

Statistical theory provides two different standards for statistical inference, the frequentist approach and the Bayesian approach. Frequentists base inference for an unknown parameter on statistical distributions derived from repeated sampling. Bayesians base inference on a posterior distribution which is derived from a combination of sample data and a prior assumed distribution (Little 2006). The estimate of the parameter obtained by using Bayesian methods can be thought of as a weighted average of the data and the prior distribution given for the parameter. When the sample size is small, much more weight is placed on the prior distribution. But when the sample size is large, the prior distribution is less important.

In recent years, Bayesian statistics have become widely used when one has reliable information about a parameter being estimated. Samaniego and Reneau (1994) demonstrated that under a variety of scenarios, Bayesian methods performed better than frequentist methods when estimating a parameter. Neath and Langenfeld (2012) showed that when a reasonable choice was used to obtain the prior distribution, Bayesian methods outperformed frequentist methods in both accuracy and precision. The use of Bayesian statistics has increased in recent years in many fields (McCarthy et al. 2004; Smyth 2004; Stoyan et al. 2000); however, the literature does not provide any examples of the use of Bayesian techniques to estimate FWD.

This study investigated the influence of the prior distribution on the standard error of the FWD estimate. When frequentist methods (that is, no prior distribution) are used, the standard error is largely based on sample size. The standard error is an important measure because it represents the precision of one's estimate. Keane and Gray (2013, p. 1104) concluded that "it appears from the results of this study that the only way to increase the precision of planar intercept and fixed-area methods is to increase sampling intensity."

We expected that using Bayesian techniques would decrease the standard error. The goal of the present study was to use planar intercept and fixed-area methods to estimate FWD loading while also incorporating prior information into the calculation. We explored whether using Bayesian methods is a viable approach to increasing precision with no additional sampling intensity and whether it would even permit a reduction in sampling intensity.

The prior information can be either photoload estimates or photo series estimates because both of these are visual estimates that can be obtained before sampling occurs. Unfortunately, the photoload estimates evaluated by Keane and Gray (2013) underestimated FWD when loadings were high. Additionally, photo series estimates were not incorporated into their study. Therefore, this study examines different prior distribution scenarios that could be used; however, we did not use the actual photoload estimates from the earlier study because these estimates were biased.

METHODS

We explored the potential for Baysesian analyses to improve precision and reduce sampling effort for two different sampling methods of fuel estimation. We assumed that the prior distribution will follow a uniform distribution. The uniform distribution requires only a minimum and maximum value as parameters, and thus, is easily obtained by skilled practitioners. We used measurements taken only from the patchy fuelbed (rather than from the uniform or jackpot fuelbeds) in the Keane and Gray (2013) study because both the planar intercept and fixed-area methods performed well for this spatial distribution.

For both the planar intercept and fixed-area methods, we examined different sampling intensities by using a bootstrapping approach with our data. Bootstrapping the data is a means of resampling the data in order to estimate the sampling distribution of a statistic. From this bootstrap distribution we can estimate the standard error of an estimator. For the planar intercept method, a bootstrap distribution was obtained for transect lengths of 200 to 900 m (every 100 m). For each bootstrap distribution, the standard error was estimated under the scenarios of no prior information (non-Bayesian) and three different uniform distributions that depended on the known fuel load. The three different uniform distributions represented a narrow, moderate, and wide range of values with "range" defined as the difference between the maximum and minimum value. The choice of the range of the prior information ("priors") was somewhat arbitrary since in practice the prior needs to be given before data collection. However, because the planar intercept performed better than the fixed-area method, we chose narrower ranges for the priors for the planar intercept method. We followed the same steps for the fixed-area plots with one exception: the sampling unit was a 1-m^2 plot rather than a 10-m transect. All statistical analyses were performed by using R (R Development Core Team 2007).

RESULTS

In general, using prior information to estimate fuel loadings significantly reduced the variability of the estimate (figs. 1 and 2, table 1). For narrow ranges, results are heavily influenced by the prior information. If one can confidently narrow the range of the estimated fuel loading, then the use of additional sampling methods does little to improve precision (figs. 1 and 2, table 1). On the other hand, if the range of possible fuel loadings is wide, there is little benefit in using Bayesian methods (figs. 1 and 2). For both the planar intercept and fixed-area methods, significant reductions in standard errors can be made by using a moderate range for the prior distribution (table 1).

For the planar intercept with a fuel loading of 0.05 kg m^{-2}, results were similar whether they were obtained when using no prior information or a wide range of priors (0.01 to 0.09 kg m^{-2}) for all transect lengths (fig. 1a). The moderate and narrow ranges resulted in standard errors much smaller than when using no prior (fig. 1a). By using a moderate range of priors (0.06 to 0.14 kg m^{-2}) for a fuel loading of 0.10 kg m^{-2}, the standard error for 200 m is about equal to the standard error for 900 m using no prior (fig. 1b). For a fuel load of 0.20 kg m^{-2}, the transect length can be reduced from 900 m to about 500 m without a change in standard error if using a moderate prior range (0.16 to 0.24 kg m^{-2}) (fig. 1d).

The results for the fixed-area method were similar to the results for the planar-intercept method (fig. 2). For very narrow range priors, the standard errors are much smaller than when using no priors (fig. 2). For the 0.05 kg m^{-2} fuel load, using a prior of between 0.02 and 0.08 kg m^{-2} reduced the standard error of the estimate from 0.019 kg m^{-2} (no prior) to 0.014 kg m^{-2} when 14 plots were used (fig. 2a, table 1). A more modest improvement in standard errors was achieved for the other two ranges (fig. 2a). The most dramatic improvement was for the fuel load of 0.20 kg m^{-2}, where all priors offered significant improvements over using no prior information (fig. 2d). For the 0.20 kg m^{-2} fuel load, the standard error could be reduced

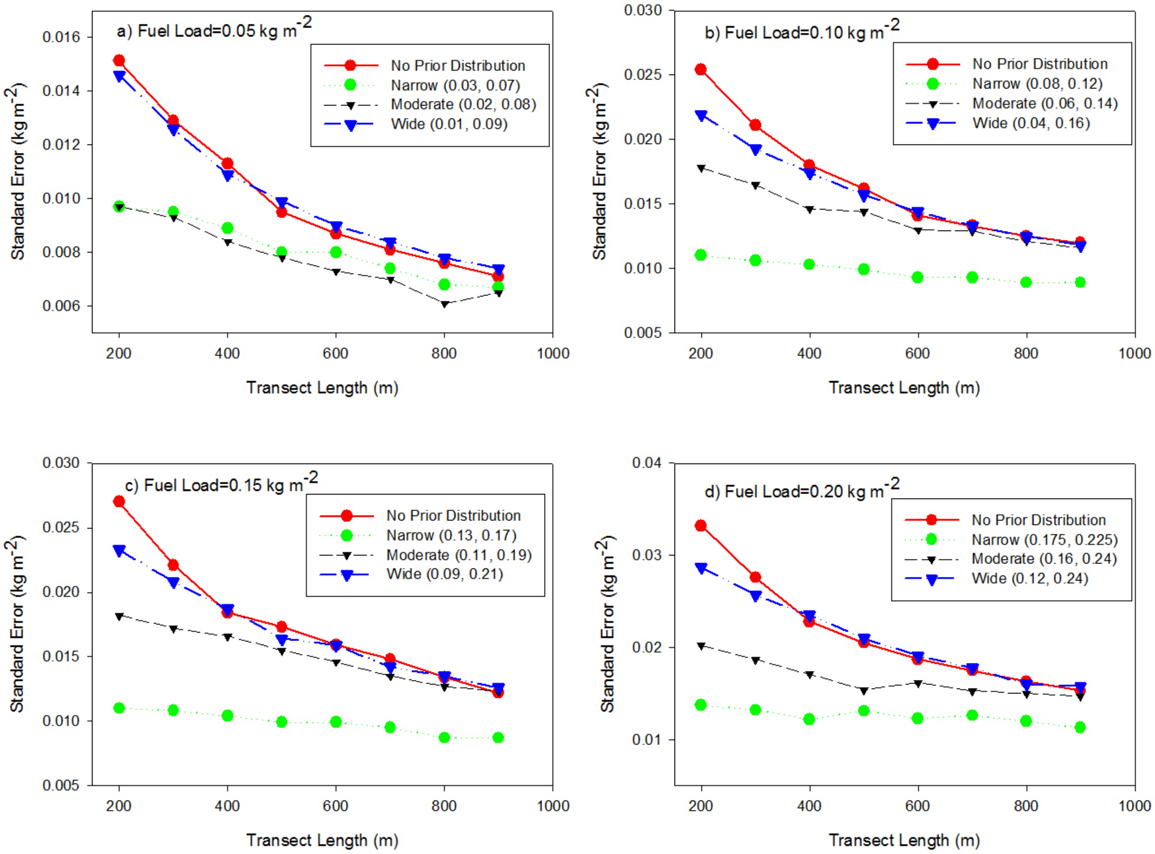

Figure 1—Relationship of standard error to distance sampled using different prior distributions and no prior distribution for the planar-intercept sampling method. For each fuel load, three different prior uniform distributions were given. The three different priors represent a wide range of possible values, a moderate range of possible values, and a narrow range of possible values.

(compared to using no prior) from 0.063 kg m^{-2} to 0.048 kg m^{-2} using a moderate prior range of 0.05 to 0.40 kg m^{-2} when sampling twenty 1-m^2 plots (fig. 2d).

DISCUSSION

This study confirms that Bayesian techniques can be used to streamline fuel loading sampling efforts by incorporating information about FWD estimates obtained via visual methods such as photoload or photo series. In general, as sampling effort increases, precision will also increase. However, using initial "good" information about the estimated fuel loading at a site can significantly increase precision as well. By obtaining quick visual fuel estimates, one can significantly reduce the sampling effort required with both the planar intercept and fixed-area methods. In fact, increasing sampling effort does not significantly increase precision if good visual estimates can be obtained.

The present study focused on examining precision rather than accuracy. Keane and Gray's (2013) study showed that the planar intercept and fixed-area methods were generally not biased; however, the photoload method underestimates fuel loading, especially for large fuel loads. Hence one should not use Bayesian approaches with photoload methods unless the accuracy of this method can be improved. As long as the prior information is unbiased and the sampling method used to collect the data is also unbiased in estimating the fuel loading, then using Bayesian methods will not decrease the accuracy of the estimator.

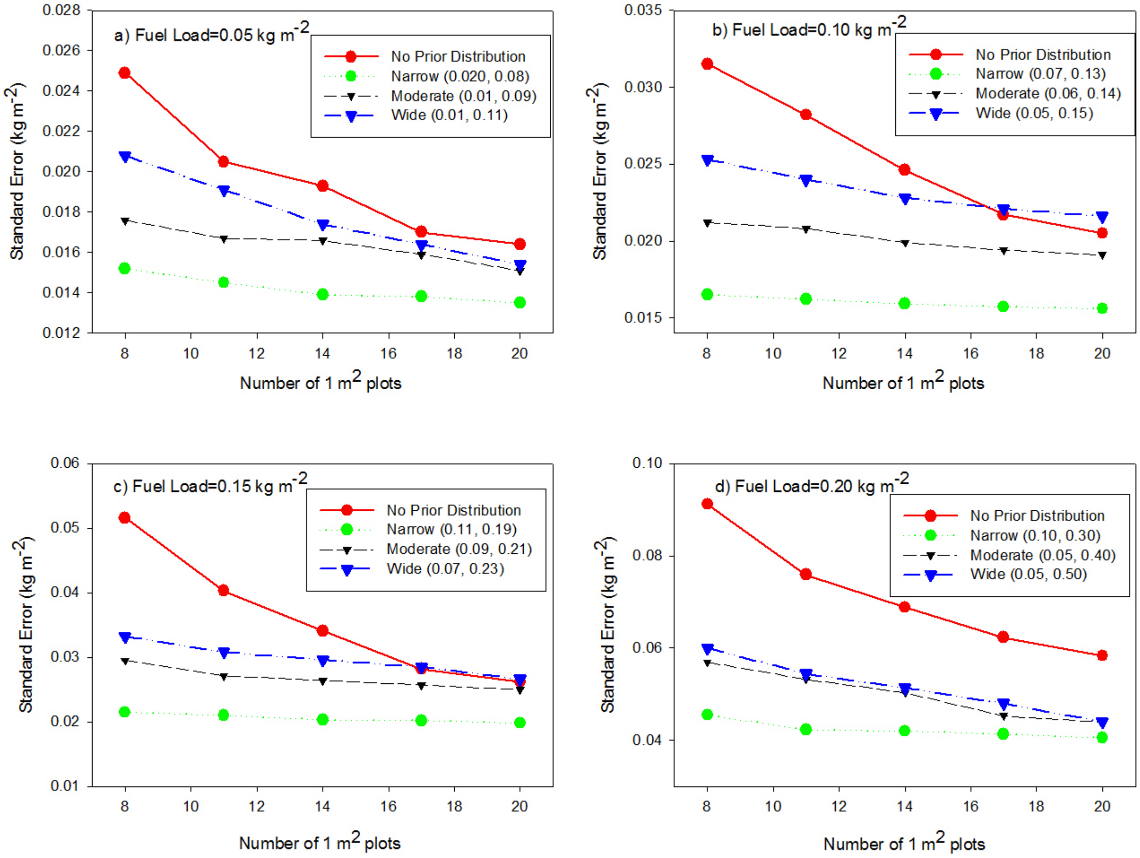

Figure 2—Relationship of standard error to number of 1-m^2 plots using different prior distributions and no prior distribution for the fixed-plot area sampling method. For each fuel load, three different prior uniform distributions were given. The three different priors represent a wide range of possible values, a moderate range of possible values, and a narrow range of possible values.

Table 1—Standard error estimates for different prior distributions when sampling 500 m using the planar intercept method or fourteen 1-m^2 plots using the fixed-area plot method.

Prior distribution[a]	Load = 0.05 kg m^{-2}	Load = 0.10 kg m^{-2}	Load = 0.15 kg m^{-2}	Load = 0.20 kg m^{-2}
Planar intercept (transect length = 500 m)				
No prior	0.0162	0.0173	0.0173	0.0205
Wide	0.0157	0.0164	0.0164	0.0210
Moderate	0.0144	0.0155	0.0155	0.0154
Narrow	0.0099	0.0099	0.0099	0.0131
Fixed-area microplot (n = fourteen 1-m^2 plots)				
No prior	0.0193	0.0246	0.0341	0.0688
Wide	0.0174	0.0228	0.0296	0.0513
Moderate	0.0166	0.0199	0.0264	0.0503
Narrow	0.0139	0.0159	0.0203	0.0420

[a] Three different prior distributions were examined. The prior distributions differed with respect to the range of possible values. For each fuel load, a wide range, a medium range, and a narrow range of values were given as a prior distribution. The ranges differed with respect to the known fuel load being estimated.

One disadvantage of Bayesian methods is that results are heavily influenced by prior distributions. Our study supported this conclusion: The standard errors for narrow-range priors did not change when fuel loading sampling effort was increased. This emphasizes the need for experts in the field to carefully obtain priors. Subsequent studies should examine the sensitivity of the prior distribution to the results of the analysis. More research is needed to further examine the possible benefits of using the Bayesian approach in sampling.

MANAGEMENT IMPLICATIONS AND CONCLUSIONS

Our results show that using prior information obtained from visual methods such as the photo series can reduce the sampling effort needed to achieve a certain precision in fuel loading sampling. This means that if fuel and fire managers have an idea of the ranges of fuel loadings before sampling, they can significantly reduce sampling time and costs by employing the Bayesian approach. However, it is of utmost importance that trained individuals determine the prior range of values because inaccurate estimations can result in inaccurate loading estimates.

ACKNOWLEDGMENTS

This material is based on work supported by the National Science Foundation under Grant No. 1156612.

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