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Bayesian Techniques for Surface Fuel Loading Estimation

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Peer Review
This work has undergone a double-blind review by a minimum of two faculty members from institutions of higher learning from around the world. The faculty reviewers have expertise in disciplines closely related to those represented by this work. If possible, the work was also reviewed by undergraduates in collaboration with the faculty reviewers.

Abstract
In previous work, researchers compared three sampling techniques for estimating the biomass of surface fine woody fuels by using them on known distributions. An important result was that precise estimates of fuel biomass required intensive sampling for both planar intercept and fixed-area methods. This study explores Bayesian statistical methods as a means to reduce the sampling effort needed to obtain a desired precision. We examined how initial estimates of the minimum and maximum fuel loading at a site could be used as prior information in a Bayesian framework. We found that, under certain scenarios, Bayesian techniques dramatically increased the precision of the estimator compared to using no prior information from the site.

Keywords
Bayesian credible intervals, surface fuel estimation, frequentist statistics

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Kupper et al.: Estimating Surface Fuel

INTRODUCTION

Accurate and precise estimates of fuel biomass are very important in fire management. Fuel biomass, defined as any forest fuel available to burn, is important when modeling smoke emissions (Hardy, Burgan, & Ottmar, 1999; Ottmar, Burns, Hall, & Hanson, 1983), soil heating (Campbell, Jungbauer, Bristow, & Hungerford, 1995), carbon stocks (Reinhardt & Holsinger, 2010), wildlife habitat (Bate, Torgersen, Wisdom, & Garton, 2004) and site productivity (Brais, Sadi, Bergeron, & Grenier, 2005; Hagan & Grove 1999). Additionally, precise fuel biomass estimates are necessary in all phases of fire management (Chen, Grady, Stephens, Villa-Castillo, & Wagner 2006; Ohlson, Berry, Gray, Blackwell, & Hawks, 2006).

Keane and Gray (2013) compared three sampling techniques for estimating fine woody (diameters < 8 cm) fuels (FWF). Their study entailed creating fuelbeds from fuels collected in the field of four known woody fuel loadings (.05, .10, .15, and .20 kg m^{-2}) and distributing these fuels over a 20 x 25 m plot. Trained technicians estimated loadings for the fine woody fuels using the photoload (Keane & Dickinson 2007), fixed-area (Keane, Gray, & Bacciu, 2012) and planar intercept (Brown 1974) methods. The photoload method uses calibrated photos of known loadings pointing toward the forest floor to visually estimate fuel loadings (Keane & 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. The fixed-area method uses a 1 x 1 m plot to define a sample frame with a fixed area and the dimensions (length, diameter) of all fuels within the plot boundary are measured to calculate volume that is then multiplied by field-estimated particle densities to estimate fuel loadings (Keane et al., 2012). The fixed-area plots are more time consuming and expensive than other methods (Keane & Gray, 2013). Finally, the planar intercept method (Brown, 1974) uses transects that are placed across the plot of interest and diameters of twigs that intersect the plane are measured. The planar intercept method has been used often because of its relative simplicity (Busing, Rimar, Stolte, Stohlgren, & Waddell, 2000; Waddell, 2001; Lutes et al., 2006). In summary, Keane and Gray (2013) found that the photoload method is the quickest method but the least accurate, underestimating FWF for almost all but the lightest loading (0.05 kg m^{-2}). It was noted that the poor performance of the photoload method might have been due to limited expertise of the technicians. The fixed-area and planar intercept methods were found to be more accurate than the photoload method, however, they were also more labor intensive. Results indicated that accurate planar intercept measurements required the use of at least 400 m of total transect to reduce variability to within 20% of the mean. A method not examined in the Keane and Gray (2013) study is 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 FWF (Sikkink & Keane, 2008). Although not examined in the Keane and Gray (2013) study, the photo series method could be used for the methods discussed in the work being presented here.

The study design of Keane and Gray (2013) provides a nice platform to study the use of Bayesian methods to estimate FWF. Bayesian methods differ from the frequentist statistics used by 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 prior study. For our purposes, we will assume that the prior information would be obtained from visual methods of estimating FWF such as the photo series method. Wright, Ottmar, & Vihnanek (2010) state that two photos from the photo series may be used to estimate loadings.

Bayesian and frequentist statistics are two different approaches to statistical inference. Frequentist statistics base inference for an unknown parameter on statistical distributions derived from repeated sampling while Bayesian statistics 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 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, however, 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) demonstrate that under a variety of scenarios, Bayesian methods perform 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 with respect to accuracy and precision. Although the use of Bayesian statistics has increased in recent years in many fields (McCarthy & Parris, 2004; Smyth, 2004; Stoyan & Penttinen, 2000), there are no examples in the literature that they have been used to estimate FWF.

In the study being presented here, we investigated the role of the prior distribution on the standard error of the FWF estimate. Using frequentist methods (no prior distribution), the standard error is largely based on sample size. It is expected that using Bayesian techniques will decrease the standard error. The standard error is an important measure because it represents the precision of an estimate. If Bayesian techniques reduce the standard error, sampling intensity could be reduced without loss of precision. The goal of this study was to use planar intercept and fixed-area plot methods to estimate FWF biomass while incorporating prior information into the calculation. In their study, Keane and Gray (2013) concluded, “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.” The present study will explore whether using Bayesian methods is a viable approach to increasing precision with no additional, or perhaps a reduction in, sampling intensity. In practice, the prior information could be determined by using the photo series or photoload method since one could obtain initial estimates of FWF before sampling occurs.

METHODS

We explored the use of Baysesian analyses to improve precision and reduce sampling effort for two different sampling methods of fuel estimation. We assumed that the prior distribution would follow a uniform distribution. The uniform distribution only requires a minimum and maximum value as parameters, and thus, is easily obtained by skilled practitioners. In practice this distribution would be the easiest for technicians especially when using the photo series method since they can bracket the fuel load between two photos (Wright et al., 2010). For our analysis, we assumed the data came from a normal model with mean μ and variance σ^2. The mean of the posterior distribution is the updated mean that takes into account both the prior

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information and the data. The posterior mean, μ^*, is calculated as follows:

$$\mu^* = \lambda \bar{X} + (1-\lambda)\left(\frac{b+a}{2}\right) \qquad (1)$$

where λ is between 0 and 1 and depends on the sample size, a and b are the minimum and maximum values from the uniform prior distribution, and $\bar{X}$ is the sample mean.

For both the planar intercept and fixed-area methods, we examined different sampling intensities by using a bootstrapping approach with our data. For the fixed-area method, the sampling unit was a 1 x 1 m plot. For the planar intercept method, the sampling unit was a 10 m transect. Bootstrapping is a means of resampling 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) where transect length represents the total length of the sampled transects. For each bootstrap distribution, the standard error was estimated. This was done under the scenarios of no prior information (non Bayesian) and three different uniform distributions which depended on the known fuel load. The three different uniform distributions represented a narrow range, a moderate range, and a wide range of values with range defined as the difference between the minimum and maximum value. These values were established based on results of a study done by Sikkink and Keane (2008) where technicians used the photo series and photoload method to estimate fuel loads. Since the planar intercept method performed better than the fixed-area method we chose narrower priors for the planar intercept method. We followed the same steps for the fixed-area plots except the sampling unit was a 1x1 m plot rather than a 10 m transect. All statistical analyses were performed using R (R Development Core Team, 2007) and JAGS (Plummer, 2003).

RESULTS

In general, using Bayesian methods to estimate fuel loadings significantly reduced the variability of the estimate (Figure 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 little improvement in precision is made by using additional sampling units (Figure 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 (Figure 1 and 2). Table 1 reports the reduction in standard error obtained by using prior distributions for 500 m of transect (planar intercept) or 14 1x1 m plots (fixed-area). For both the planar intercept and fixed-area, significant reductions in standard errors can be made by using a moderate range for the prior distribution (table 1).

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

The results for the fixed-area method were similar to the results for the planar-

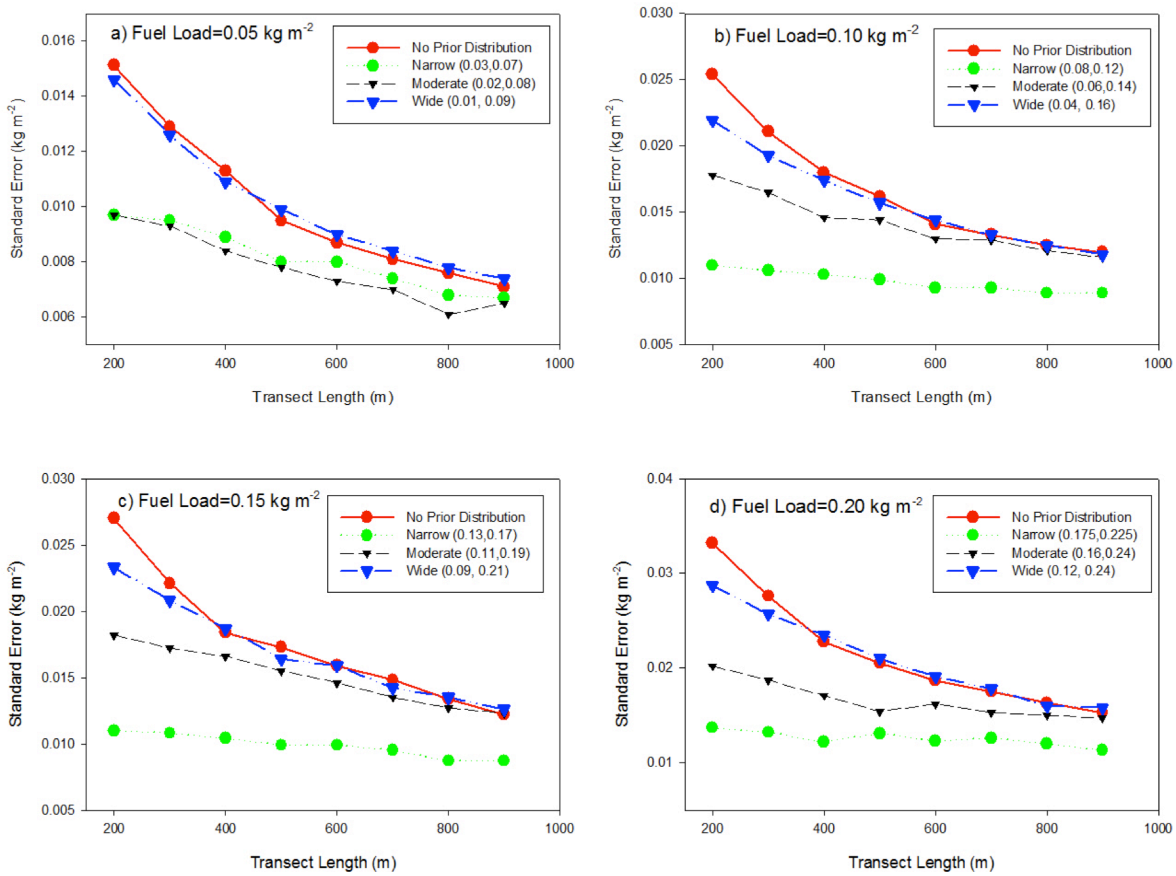

Figure 1. The effects of planar-intercept sampling intensity (total transect length) and statistical technique (non-Bayesian vs. Bayesian) on the standard error of estimated surface fuel loads from four known fuel loads sampled: 0.05 (a), 0.10 (b), 0.15 (c), 0. (d) kg m^{-2}. No prior distribution was used for the non-Bayesian analysis and three prior estimates for the range of fuel loading (narrow, moderate, wide) were used for Bayesian analyses.

intercept method (Figure 2). For very narrow range priors, the standard errors are much smaller than using no priors (Figure 2). For the 0.05 kg m^{-2} fuel load, using a narrow prior of 0.02 to 0.08 kg m^{-2} reduced the standard error of the estimate from 0.0193 kg m-2 (no prior) to 0.0139 kg m-2 when 14 plots were used (Figure 2a, Table 1). A more modest improvement in standard errors was achieved for the other two ranges (Figure 2a). The most dramatic improvement was for the highest fuel load of 0.20 kg m^{-2} where all priors offered significant improvements over using no prior information (Figure 2d). For the 0.20 kg m^{-2} fuel load, the standard error could be reduced (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 20 one m^2 plots (Figure 2d).

DISCUSSION

This study confirms that Bayesian techniques can be used to streamline fuel loading sampling efforts by incorporating information about FWF estimates obtained via the photo series method. 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

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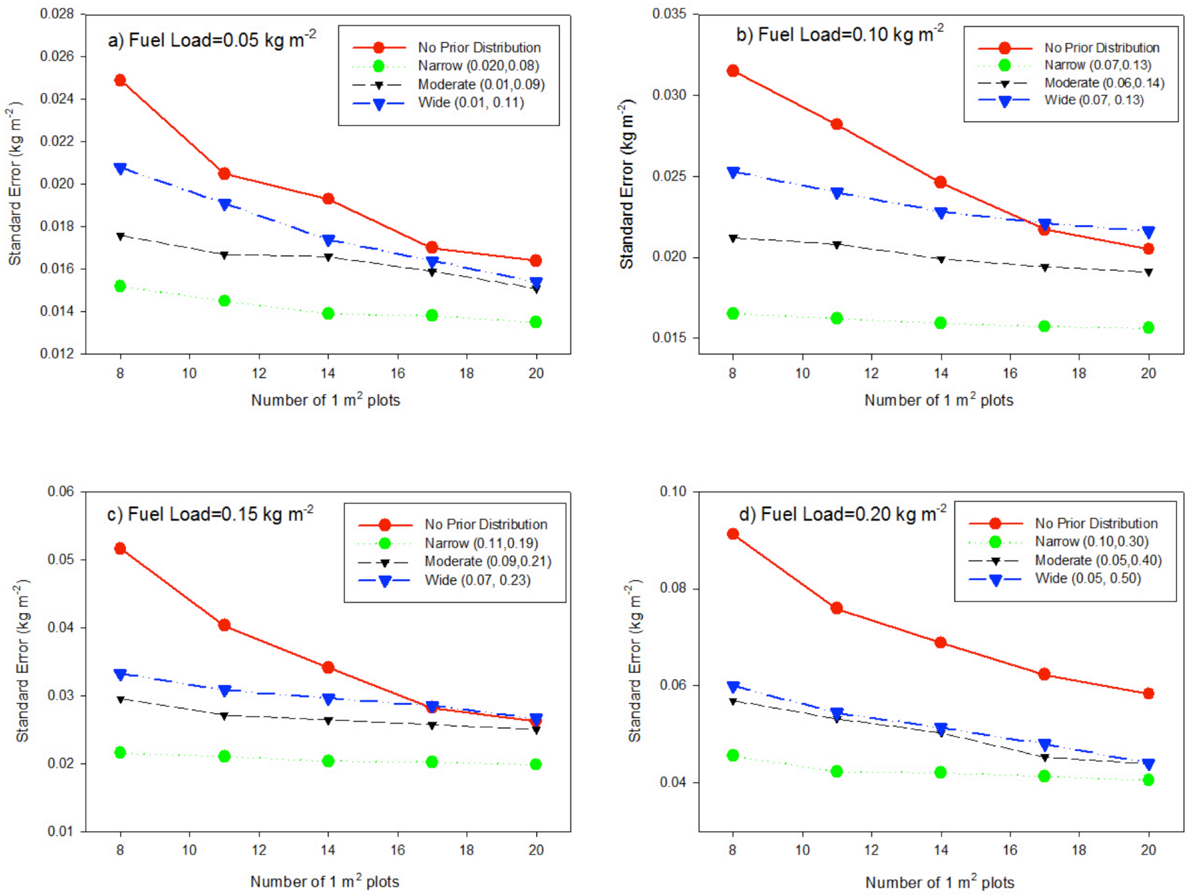

Figure 2. The effects of fixed-area plot sampling intensity (number of plots) and statistical technique (non-Bayesian vs. Bayesian) on the standard error of estimated surface fuel loads from four known fuel loads sampled: 0.05 (a), 0.10 (b), 0.15 (c), 0. (d) kg m^{-2}. No prior distribution was used for the non-Bayesian analysis and three prior estimates for the range of fuel loading (narrow, moderate, wide) were used for Bayesian analyses.

intercept and the fixed-area methods. In fact, increasing sampling effort does not significantly increase precision if good visual estimates can be obtained. Results of this study show that this approach can be applied as an alternative to increasing sampling effort. One disadvantage of Bayesian methods is that results are heavily influenced by prior distributions. This is evident as the standard errors for narrow range priors do not change when sampling effort is increased. This emphasizes that experts in the field must carefully obtain priors.

Although more research should be done to examine the possible benefits of using the Baysian approach, it is clear from these results that using prior information obtained from visual methods such as the photo series can reduce the sampling effort needed to achieve a certain precision. It is of upmost importance that trained individuals determine the prior range of values and further studies should examine the sensitivity of the prior distribution to the results of the analysis.

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Prior distribution	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=14 1m^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

Table 1. Standard error estimates for different prior distributions when sampling 500 m using the planar intercept method or 14 one m^2 plots using the fixed-area plot method.

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