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The Evaluation of Meta-Analysis Techniques for Quantifying Prescribed Fire Effects on Fuel Loadings

Karen E. Kopper, Donald McKenzie, and David L. Peterson

Authors

Karen E. Kopper is a fire ecologist, North Cascades National Park, 7280 Ranger Station Road, Marblemount, WA 98267; **Donald McKenzie** is a research ecologist and **David L. Peterson** is a research biologist, U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station, Pacific Wildland Fire Sciences Laboratory, 400 N 34th Street, Suite 201, Seattle, WA 98103.

Cover photographs by Garrett Boarts, North Cascades National Park,
7280 Ranger Station Road, Marblemount, WA 98267.

Abstract

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Models and effect-size metrics for meta-analysis were compared in four separate meta-analyses quantifying surface fuels after prescribed fires in ponderosa pine (*Pinus ponderosa* Dougl. ex Laws.) forests of the Western United States. An aggregated data set was compiled from 8 published reports that contained data from 65 fire treatment units. Downed woody and organic fuels were partitioned into five classes, and four meta-analyses were performed on each in a 2 by 2 factorial combination of fixed-effects vs. mixed-effects models with a difference-based metric (Hedges' *d*) vs. a ratio-based metric (log-response ratio). All analyses yielded significant effect sizes for each class of fuels, although mixed-effects models had larger confidence intervals around mean effect sizes and smaller ranges in those means. The use of multiple methods produced a robust result for this study, but also carries the danger of selective interpretation if results are contradictory. Meta-analysis in fire research merits further consideration because it facilitates inferences across data sets reported by multiple authors, even when reporting is inconsistent. Nevertheless, standardized methodology, consistent measurement protocols, and complete reporting of both significant and nonsignificant results will greatly assist future synthesis efforts using meta-analysis.

Keywords: Effect size, fuel treatment, Hedges' *d*, log-response ratio, mixed-effects model.

Summary

The wealth of studies on prescribed fire provides ample opportunity to examine its effect on fuels, but the utility of these studies depends on our ability to reconcile their multiple approaches to data collection and analysis. Meta-analysis is a powerful technique used to analyze large data sets obtained from multiple sources and different sampling techniques, and is widely used in the social and medical sciences.

We performed four different meta-analyses of published fire effects data in which we compared the effect sizes of prescribed fire treatments on the fuel loads of five fuel-size classes of downed wood collected before and after prescribed fires. We compiled fuel loading statistics from 8 studies from the literature comprising 65 treatment units. To compare different meta-analysis test statistics, we used a 2 by 2 factorial design of fixed-effects vs. mixed-effects models with a difference-based metric (Hedges' *d*) vs. a ratio-based metric (log-response ratio).

Prescribed fire produced a significant fuel reduction effect for each of the fuel-size classes in all of the meta-analyses, but the amount and variance of the effect sizes differed per analysis. The fixed-effects models had significant heterogeneity within and between their fuel-size classes, which we explored through categorical subanalyses within the fuel-size classes using techniques similar to ANOVA. We partitioned each fuel-size class by season and also separated the large-diameter fuels into solid and rotten categories. The meta-analyses performed with the mixed-effects model, which assumes and accounts for random variation among observations, reduced the heterogeneity between the fuel-size classes but did not permit categorical subanalyses.

All of the models confirmed that fuel reduction was significant for each fuel-size class, suggesting that our analysis was robust to the choice of model with respect to the overall effect. The mixed-effects models may be intuitively more appropriate for the analysis of ecological data owing to their incorporation of random variation, but in the process of stabilizing variance, the mixed-effects models bypassed the potentially informative processes of the categorical meta-analyses performed in the fixed-effects models. Although the use of multiple models produced consistent results with respect to the overall effect in our study, we recognize how the use of multiple models could enable the selective interpretation of results. We suggest that the data and the research questions of interest should inform not only the choice of sampling design and the standardization of data collection, but also the choice of effect-size metrics and analytical methods.

Introduction

An observant hiker, naturalist, or outdoor enthusiast is bound to encounter tree tags, duff pins, or plot stakes in the forest owing to the large number of forest research plots that have been installed by scientists over the past several decades. Although many of the methods used to collect and analyze fire effects data have been refined over the years, the information from each individual study is still unique and potentially valuable. Meta-analysis is a statistical technique for synthesizing data from multiple studies, and is robust to data sets of different sizes and formats. However, meta-analysis has only recently been applied to natural resources data (e.g., Johnson and Curtis 2001), and appropriate techniques for its application are still being tested by biologists and statisticians.

Analogous to analysis of variance (ANOVA), treatments in meta-analysis are compared to a control via the testing of a "null" hypothesis. Replicates in the ANOVA correspond to individual studies in meta-analysis. The magnitude of the treatment effect is expressed by the **effect size**, a dimensionless measure of the difference between a control and treatment group used to express the combined results from multiple studies in meta-analysis (Cohen 1969). The advantage of the effect size is that it is usually standardized and relatively scale-free, and therefore independent of the size or units of the individual studies that are combined (Cohen 1969, Glass et al. 1981, Hedges and Olkin 1985). There are three general categories of effect-size metrics: difference-based, ratio-based, and correlation-based indices (Rosnow and Rosenthal 2003). Each type can be used in raw form (generally not an option in meta-analysis), standardized, or transformed (e.g., logarithmically).

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Interpretations of heterogeneous groupings of ecological data sets have until recently been based on expert opinion and other forms of qualitative analyses such as omnibus tests or vote-counting procedures that do not provide quantifiable measurements of effect (Gurevitch and Hedges 2001). Furthermore, the assumptions of statistical tests such as ANOVA and regression analyses are often violated when these techniques are used for research synthesis, in which multiple studies with substantial heterogeneity of variance and sample size are the norm (Hedges and Olkin 1985).

Modern meta-analysis originated in the medical and behavioral sciences in the 1970s (Glass 1976, Rosenthal 1976) as a means to synthesize the results of up to several hundred studies (Glass et al. 1981). New meta-analytic procedures have developed in response to the often more heterogeneous experimental environments of the social sciences and behavioral research compared to those of classical biomedical studies (Glass et al. 1981, Hedges and Olkin 1985, Rosenthal 1984). For example, besides calculating the significance of the effect size, Hedges (1982) proposed the use of chi-square tests of homogeneity to measure the degree of heterogeneity in the model, thereby also gauging the appropriateness of combining groups within or among study sets (Hunter and Schmidt 1990). Tests for homogeneity are now recognized as powerful tools to evaluate the efficacy of meta-analytic designs in the social and medical fields (Cook et al. 1992, Hardy and Thompson 1998).

The potential usefulness of meta-analysis in natural resources has been recognized only relatively recently. There are 33 meta-analyses in ecology listed in the AGRICOLA searchable database (National Agricultural Library 2008) between the years 1992 and 2006, with the majority published since 2001. Much of the interest was generated after a landmark meta-analysis of biological communities (Gurevitch et al. 1992) quantified the magnitude of interspecific competition, differentiating treatment effects on the biomass of 93 species of various trophic levels, and inhabiting environments ranging from terrestrial to aquatic.

At that time, meta-analysis used only a fixed-effects model, which assumes that the treatment effect does not differ across studies. More recently, however, as the potential usefulness of meta-analysis in natural resources has been recognized, random-effects and mixed-effects models, which characterize mean effect size as a random variable, have been adapted for meta-analyses (Cooper and Hedges 1994, Gurevitch and Hedges 1993, Hedges 1982, Stram 1996). Gurevitch and Hedges (1999) suggested that the mixed-effects model may be especially useful for meta-analyses in the field of ecology, considering the random variation inherent in biological systems. However, the appropriate use of meta-analysis techniques to interpret highly variable biological systems remains a point of debate among ecologists and statisticians (Fernandez-Duque and Valeggia 1994, Gurevitch and Hedges 1999, Osenberg et al. 1997). The pioneering meta-analysis by Gurevitch et al. (1992) found a significant overall effect of competition on biomass coupled with high heterogeneity using the fixed-effects model. With the diversity of ecological processes now under investigation, the appropriate statistical model and the choice of metrics used to calculate effect size are both subject to further review.

Using a fixed-effects model with the *ln*R metric of effect size, Wan et al. (2001) performed the only previous meta-analysis of fire effects. This meta-analysis measured change in concentrations of nitrogen (N), ammonium, and nitrate in soils and fuels after fire, comparing prescribed burning, slash burning, wildfire effects, and time since fire. Fire was found to significantly reduce the amount of N and increase soil ammonium and nitrate pools in fuels, but did not have a significant influence on N concentrations in fuels or on soil properties. Inconsistency of sampling depth was considered to be an underlying factor in the heterogeneous influence of fire on soil N pools. Other factors not addressed in the meta-analysis were also thought to influence postfire N properties in soils; these included soil moisture, plant uptake, N deposition, leaching, and erosion (Wan et al. 2001).

Fire exclusion is one of the primary causes of hazardous fuel accumulations in many ponderosa pine (*Pinus ponderosa* Dougl. ex Laws.) forests in western North America (Agee 1993). In response to decades of fire exclusion, managers are now using prescribed fire and thinning treatments to reduce fuels in these forests. Accurate quantification of fuel-load reduction after prescribed burning is essential for evaluating the success of fuel treatments.

In this study, we test for significant fuel-load reduction after prescribed fire with meta-analysis of published literature, and check the robustness of our results by using two common metrics of effect size (Hedges' *d* and the log-response ratio) in combination with two statistical models (fixed effects and mixed effects). Meta-analysis was limited a priori to ponderosa pine under the assumption that including additional forest types would increase the variability in fuel loading, thereby reducing our ability to identify differences among our models as effectively. There is also a relatively large volume of literature on fire effects in ponderosa pine. Response variables were limited to five types of surface fuels because these are the most commonly reported and we needed adequate replication given that we expected substantial heterogeneity among studies.

Methods

The effect-size metrics used for social and medical research syntheses are often modified for use in the field of ecology, but the general principles of meta-analysis remain the same. The standard procedure begins with a comprehensive literature search (literature on fuel reduction in this case) and the extraction of summary statistics from each individual study. Summary statistics are then used to derive the effect size and variance of each individual study (summary statistics are in app. 1). The statistical significance of effect size measures the degree of departure from the null hypothesis (Cohen 1969). The grand mean effect (E) and variance (s^2_E) of the treatments are derived from a weighted average of the individual effect sizes and their variances, respectively, where studies with larger sample sizes are given more weight.

A significance test of the homogeneity of the individual effect sizes is performed using a Chi-squared test (similar to the test for homogeneous variance in ANOVA). If the null hypothesis of homogeneity is not rejected, indicating that there is little heterogeneity of the effect sizes of the individual studies, then the meta-analysis is complete and the results of the effect size measurement are considered "conclusive."

On the other hand, if there is significant heterogeneity of the effect sizes, then the individual studies are separated into groups according to shared properties determined by the analyst, and a "categorical" meta-analysis is performed. The categorical meta-analysis is a powerful method of comparing the effect of the treatment on various arrangements of individuals grouped with respect to physiological, spatial, temporal, or environmental differences. For example, we expected prescribed fire might have different effects on fuels in ponderosa pine systems of the very arid Southwest versus the moderately arid inland Pacific Northwest.

The iterative process of classification into homogeneous subsets continues until there is no longer a significant difference between groups, in which case the meta-analysis proper is conducted within groups, with a test of significance of the within-class effect size (Wan et al. 2001). If there are not sufficient data available to perform the categorical analyses, then the results of the meta-analysis, including the effect sizes, are considered "inconclusive."

Literature Search

A comprehensive search of the journal articles that provided summary statistics on fuel-load reduction in ponderosa pine ecosystems of the Western United States was performed through keyword searches (fire, pine, fuel) in the Agricultural Online Access database (AGRICOLA©, SilverPlatter Information, Inc., Norwood, MA) of published research. Five selection criteria were imposed sequentially: (1) all published reports with a sample size greater than one, (2) a documented control or pretreatment fuel loading, (3) a postburn or percentage reduction of fuel measured within 1 year of prescribed fire, (4) size classes that could be matched to lag-time fuel classes, and (5) adequate information to derive summary statistics. Although more than 40 journal articles specifically addressed fuel reduction in ponderosa pine forests, only 8 published articles (table 1) contained adequate statistical summary information for meta-analysis of the reduction of organic (combined litter and duff) or downed woody fuels. Another eight studies addressing organic or woody fuel reduction in ponderosa pine forests could not be used for the meta-analysis because they do not report sample size or any measure of variability (confidence intervals, standard deviation, or standard error).

Analysis of fuel reduction was not the primary purpose of many of the studies used in this meta-analysis, but was often reported in conjunction with analysis of soil nutrient properties (Kovacic et al. 1986, Landsberg et al. 1984), as a measure of comparison between various fire management techniques (e.g., Kalabokidis and Wakimoto 1992), or as background information regarding other prescribed fire effects (e.g., Busse et al. 2000).

Table 1—Summary of information contained in articles used in the meta-analysis

Source of study	Forest type (location)	Preburn site conditions	Fuel variables[a]	Treatments (replicates)[b]
Busse et al. (2000)	Ponderosa pine (Fremont National Forest, Oregon)	53 to 83 years old, second growth	Organic, 100-hr, ≥1,000-hr fuels; spring burn	1 (14)
Davis et al. (1964)	Ponderosa pine (Coconino National Forest, Arizona)	Pole-size trees with scattered old growth	Organic; fall burn	1 (2)
Kalabokidis and Wakimoto (1992)	Ponderosa pine/Douglas-fir (western Montana)	Multiaged selection cut	Organic, 1-hr, 10-hr, 100-hr fuels; fall burn	2 (30)
Kauffman and Martin (1989)	Mixed conifer (Blodgett Forest Research Station; Challenge Experimental Forest, Plumas National Forest; both in California)	Blodgett: 70 years old Challenge: 110 years old	Organic, 1-hr, 10-hr, fuels; 100-hr, ≥1,000-hr fall and spring burns	8 (5)
Kovacic et al. (1986)	Ponderosa pine (Jemez Springs, New Mexico)	Multiaged	Organic; winter burn	3 (5)
Landsberg et al. (1984)	Ponderosa pine (Deschutes National Forest, Oregon)	Precommercial thin 18 years earlier, slash remaining	Organic; spring burns of varied intensity	2 (2)
Sackett and Haase (1998)	Ponderosa pine (Fort Valley Experimental Forest, northern Arizona)	Multiaged, fire suppressed	Organic, 1-hr, 10-hr, 100-hr, ≥1,000-hr fuels; fall burn	2 (3[c])
Sweeney and Biswell (1961)	Ponderosa pine with black oak/Douglas-fir (Lake County, California)	Open stand, prescribed fire 3 to 8 years earlier	Organic; spring burn	1 (4)

[a] Fuel variables are described in the text.
[b] Each treatment is a discrete burn within which there were two or more replicate sites where data were collected.
[c] Three replicates for all except the organic, which has 18 replicates.

Although all studies used in the meta-analysis reported fuel reduction after prescribed fire, the season of burns differed and the preburn status of the study areas differed by density of trees and ratio of ponderosa pine to other conifer species. The most commonly reported statistic was organic layer (combined litter and duff) reduction. A brief summary of the characteristics of the studies included in the sample is presented in table 1.

Summary Statistics

Summary statistics were extracted from the studies and recorded on Microsoft Excel[1] spreadsheets. All of the meta-analysis calculations other than summary statistic extraction were performed with MetaWin 2000 statistical software designed specifically for meta-analysis (Rosenberg et al. 2000).

[1] The use of trade or firm names in this publication is for reader information and does not imply endorsement by the U.S. Department of Agriculture of any product or service.

The summary statistics required for both Hedges' *d* and the log response ratio *ln*R are the sample size, mean, and standard deviation. The extraction of summary statistics for effect-size calculations was the most time-consuming process in the performance of this meta-analysis. The calculations used for this process are consistent with basic statistical principles for deriving standard deviations, means, and sample sizes (Glass et al. 1981) (see appendix). Meta-analysts should maintain spreadsheets and include summary statistics used when reporting results, not only for the benefit of the meta-analyst, but to allow for reanalysis and interpretation by others (Gurevitch et al. 1992, Wan et al. 2001).

The number of studies (N) and distinct treatment units (*n*) used as summary statistics in the meta-analysis were the number of independent prescribed burns (N) and the number of independent transects or replicates (*n*). These values were inferred from the methodology section of the journal articles and did not always concur with the sample sizes reported by the authors. The numbers of individual samples along transects or within plots were used to verify the number of replicates and derive missing error terms. In several instances the individual samples along transects were not reported, and other reports were suspect of pseudo-replication.

Calculation of fuel loads was broken down into several size classes for the meta-analysis, because we expected that prescribed fire would have different effects on different sizes of surface fuel. The size classes representing the diameter of the fuel are defined according to the U.S. National Fire Danger Rating System (Deeming et al. 1977) into time-lag classes of 1 hr (0 to 0.25 in [0 to 0.64 cm]), 10 hr (0.25 to 1 in [0.64 to 2.54 cm]), 100 hour (1 to 3 in [2.54 to 7.62 cm]), and 1,000 hr and greater (≥3 in [≥7.62 cm]). The time lag indicates the amount of time required for the moisture content of a fuel of a given size class to move about two-thirds of the way to a new equilibrium moisture content. The 1,000-hr time-lag class is stratified into rotten (1,000r) and sound (1,000s) wood categories.

Maintaining independent summary statistics and studies is a dilemma for meta-analysts. If independence in the response variable is violated, it will inflate the significance levels for statistical tests (Wan et al. 2001). Nonindependence arises through the collection of multiple measurements on the same sample (Gurevitch et al. 1992) or the inclusion of more than one result from a single study (Wan et al. 2001). The sampling techniques used to measure the litter (or O_l horizon) and duff (or O_e and O_a horizons) often have the potential to violate independence. When the planar intercept technique is used to sample litter and duff, the surveyor estimates the division between these two layers at the same sample point. This delineation is subjective enough to create the potential for substantial error between the pre- and posttreatment values designated as litter or duff.[2] Therefore, measurements reported for litter and duff were consolidated into one value (organic) to maintain independence.

The sampling techniques used in ground-fuel analysis complicate the process of extracting the summary statistics in other ways. For example, the values for the total fuel (organic and woody debris) and total woody debris could not be included in this analysis because only a few studies provided these statistics as a combined total. The individual values reported in the majority of the studies could not be combined because they did not share a common sample size. Instead, downed woody debris was measured along a transect as a continuous predictor, and litter and duff were measured at individual points using the planar intersect technique (Brown 1974) or within various-sized units.

Conversion factors were sometimes required to report the summary statistics of the organic (litter and duff) layer, despite the dimensionless quality of Hedges' *d* or *ln*R. Typically, the litter and duff components are both recorded as measurements of depth, allowing the sample size and standard deviation of each to be combined and used as summary statistics directly. In some instances, however, duff was reported in units of mass, and litter was recorded in units of depth. We used a conversion factor from Brown (1974) where necessary to combine the two categories.

Metrics of Effect Size

There are several metrics that have been thoroughly examined for use in meta-analysis (Rosenberg et al. 2000). We chose the two that are most widely used in ecology: Hedges' *d*, a standardized difference-based method, and the log response ratio, *ln*R, a transformed ratio-based method (Rosnow and Rosenthal 2003).

Hedges' *d*

Hedges' *d* (eq. 1) estimates the standardized mean difference in a manner similar to Glass's (1976) original effect size measurement, and is the most widely accepted measure of effect size used in the social sciences (Hedges and Olkin 1985).

$$d = [(Y_e - Y_c)/s]\, J(\mathrm{m}) \tag{1}$$

where Y_e and Y_c are the means of the treatment (e) and control (c) groups, s is the pooled standard deviation, and J(m) is a correction factor to remove small-sample bias.

[2] Kopper, K.E. 2007. Personal communication. Fire ecologist, North Cascades National Park Service Complex, 7280 Ranger Station Road, Marblemount, WA 98267.

The difference between the mean of the treatment group (Y_e) and the mean of the control group (Y_c) is divided by the pooled standard deviation s, providing effect size, a dimensionless statistic. As a rule of thumb, 0.2 is a “small” effect, 0.5 is a “medium” effect, 0.8 is a “large” effect, and any effect greater than 1.0 is “very large” (Cohen 1969). The variance of Hedges’ *d* permits the calculation of confidence intervals around the effect size.

Equation 2 is the variance of Hedges’ *d*,

$$\text{Variance of } d = s^2 (d) = [(N_c + N_e)/N_c N_e] + d^2/2(N_c + N_e) \qquad (2)$$

where N_c and N_e are the total number of samples (Σn_{ij}) in the control and treatment group, respectively (Hedges and Olkin 1985).

Equations 3 and 4 are for the pooled standard deviation and correction factor, respectively:

$$s = [(N_e - 1)(s_e)^2 + (N_c - 1)(s_c)^2]/(N_e + N_c - 2) \qquad (3)$$

where s_e and s_c are the standard deviations of the individual samples, and

$$J(\mathrm{m}) = 1 - (3/(4\mathrm{m} - 1)) \qquad (4)$$

where $\mathrm{m} \approx N_c + N_e - 2$ (Rosenberg et al. 2000).

There are potential problems with Hedges’ *d*. Osenberg et al. (1997) pointed out that *d* is sensitive to the differences in sample standard deviations, rather than the actual strength of the process. For example, in two studies measuring the effect of different predators on the same prey, one predator may appear to have a larger effect size, but in reality *d* is larger because the studies compiled for that predator had smaller s values than studies compiled for the other.

Log Response Ratio

Although no single metric of effect size is optimal for all cases, the use of the log response ratio and its variance (eqs. 5 and 6) is currently favored in the meta-analyses of ecological data (Hedges et al. 1999, Suding 2001, Wan et al. 2001).

$$In\mathrm{R} = \mathrm{In}\ (Y_e/Y_c) \qquad (5)$$

$$\text{Variance of } In\mathrm{R} = [(s_e)^2/N_e (Y_e)^2] + [(s_c)^2/N_c (Y_c)^2] \qquad (6)$$

where the notation is consistent with that used for Hedges’ *d*.

The log response ratio estimates the proportional change between the treatment and control groups (Rosenberg et al. 2000), thus allowing the fuel reduction effect to be derived from the back-transformed log response ratio. Hedges et al. (1999) presented the statistical properties of the log response ratio and exemplified its appropriate usage in meta-analysis. The log response ratio can only be used for data that can be expressed as a ratio, and where the denominator (mean of the control group) is not zero or opposite of the overall effect (e.g., if the fuel load increased instead of decreased in this study, then this metric could not be used).

Natural logarithmic transformations of the response variable are commonly used in ordinary regression models for biological systems to stabilize variance. Heterogeneous variance is likely in most ecological studies evaluating response over large geographic areas. *ln*R is also appropriate when the change agent acts exponentially (Suding 2001), which is, however, not generally the case for fire effects.

Models for Meta-Analysis

A fixed-effects model carries the assumption that all of the variation in effect sizes is due to sampling error (Gurevitch and Hedges 2001). In contrast, a mixed-effects model partitions the heterogeneity within and among groups into that from fixed and random effects, respectively (e.g., treatment and site).

The mixed-effects model is often more appropriate for ecological studies in which it is not assumed that a population of responses, such as fuel size classes, share a common true effect size across studies (Gurevitch and Hedges 2001). In a fixed-effects model, all the differences within the size classes would be assumed to be due to sampling error, whereas in a mixed-effects model, random variation among studies is expected. In this meta-analysis, the individual studies differed geographically and ecologically, suggesting that a mixed-effects model might be more appropriate. We wanted to test the sensitivity of our results to model type, however, so fixed-effects models were also employed.

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Homogeneity Tests

The equality of the individual effect sizes from each study is measured with the homogeneity Q test statistic. This statistic has an approximate χ^2 distribution with n–1 degrees of freedom, and tests the null hypothesis that all of the effect sizes are equal (Gurevitch and Hedges 2001). The larger a Q value is, the greater the heterogeneity. In categorical studies (multiple classes), total heterogeneity Q_T can be partitioned into between-class heterogeneity Q_B and within-class heterogeneity Q_W in a manner analogous to ANOVA. The former test statistic measures the variation in effect sizes explained by the model, and the latter measures the residual error variance that is not explained by the model (Rosenberg et al. 2000). The within-class heterogeneity is not quantified for mixed-effects models owing to the inherent variation within them. If the effect sizes are not too large and there are at least 10 samples per class, then the homogeneity test is fairly robust (Hedges and Olkin 1985).

Results

Fixed-Effects Model With Hedges' *d*

The effect sizes for each time-lag class are significant (fig. 1), although the 100-hr size class was barely so. Differences between the classes are also significant (Q_B = 36.46, P(X^2) < 0.001). Interestingly, the fuel-reduction effect appears to be greater (in absolute) for the 1,000-hr time-lag class than for the smaller diameter 10-hr and 100-hr time-lag classes. One explanation for the higher consumption of large downed logs (≥1,000-hr fuels) is that small-diameter fuels and organic material that had accumulated around them were smoldering, thus promoting their combustion. This interpretation is consistent with the even greater reduction in organic and 1-hr fuels, which could also have provided continuity between the piles and accumulated at the bases of standing trees.

There is significant heterogeneity within the individual fuel time-lag classes (Q_W = 204.06, P (X^2) < 0.001). To explain these differences in treatment effects within a time-lag class, the ≥1,000-hr fuels were partitioned into "solid" and "rotten" to determine whether there is a relationship to fuel compactness (table 2). This partitioning reduced heterogeneity within and between the studies

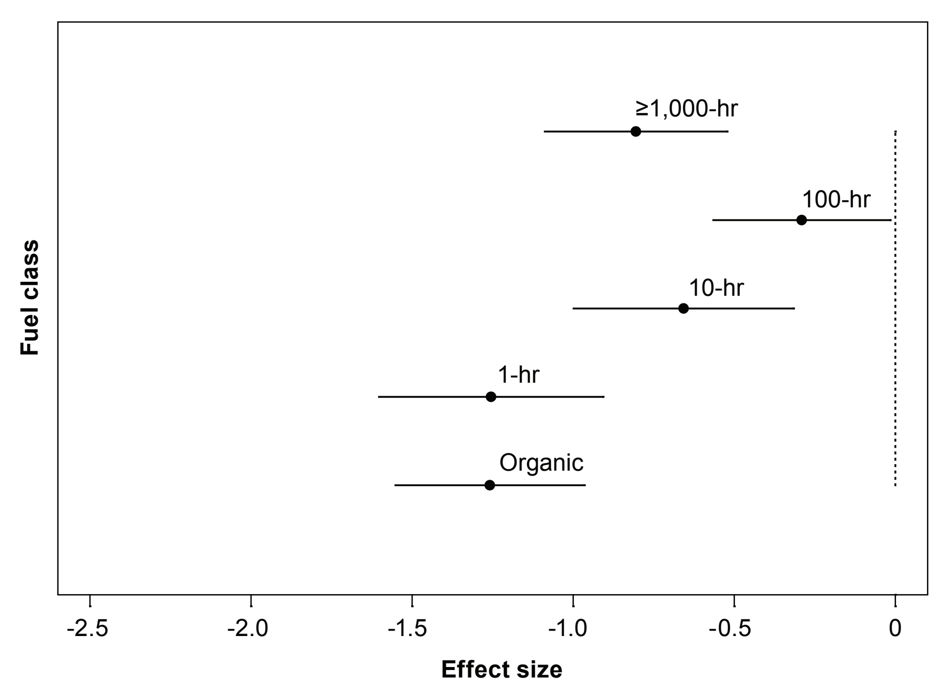

Figure 1—Fixed-effect model using Hedges' *d* as the metric of effect size with 95-percent confidence interval. Total heterogeneity Q_T = 240.52 (P(X^2) < 0.001), between-class heterogeneity Q_B = 36.46 (P(X^2) < 0.001), and within-class heterogeneity Q_W = 204.06 (P(X^2) < 0.001) are all significant.

Table 2—Heterogeneity tests and mean effect sizes using a fixed-effects model with Hedges' *d* to partition the >1,000-hr fuel class into categories of solid (1,000s) and rotten (1,000r)

	Heterogeneity		
Model	df	Q	P X^2
Between	1	2.02	0.16
Within	18	28.84	0.05
Total	19	30.85	0.04

	Mean effect size			
Size class	N	*E*	df	95% CI
1,000s	10	-0.22	9	-0.65 to 0.21
1,000r	10	-0.60	9	-1.03 to -0.17
Total	20	-0.41	18	-0.69 to -0.13

to nonsignificant levels simultaneously, yet the total heterogeneity of the model remained significant. This indicates that the differences between solid and rotten fuels do not influence the degree of fuel reduction expressed in the analysis, although other sources of variation may exist.

The only other source of variation that could be explored further, given the small number of samples for all other factors, was the potential influence of season on fuel-load reduction. The categorical analysis of fuel reduction comparing spring and fall prescribed burns (table 3) did not successfully reduce the total heterogeneity in any of the individual fuel-class categories. Instead, the analyses were either terminated or inconclusive. The meta-analysis is "terminated" if there are not significant differences between the categories (spring and fall, in this case) but the total heterogeneity remains significant. The meta-analysis is "inconclusive" when between-class

Table 3—Summary results of heterogeneity tests using the fixed-effects model with Hedges' *d* for the categorical analysis of burning season (spring versus fall) on fuel reduction

	Test results (Q)			
Fuel class	Between	Within	Total	Result[a]
Organic	10.92 $P(X^2) = 0.004$	63.99 $P(X^2) < 0.001$	74.92 $P(X^2) < 0.001$	Inconclusive
1-hr	0.22 $P(X^2) = 0.642$	19.17 $P(X^2) = 0.024$	19.39 $P(X^2) = 0.036$	Terminated
10-hr	7.66 $P(X^2) = 0.006$	45.15 $P(X^2) < 0.001$	52.81 $P(X^2) < 0.001$	Inconclusive
100-hr	1.57 $P(X^2) = 0.210$	29.05 $P(X^2) = 0.002$	30.62 $P(X^2) = 0.002$	Terminated
≥1,000-hr	0.002 $P(X^2) = 0.961$	26.32 $P(X^2) = 0.006$	26.33 $P(X^2) = 0.010$	Terminated

[a] See text for explanations of "inconclusive" and "terminated."

heterogeneity is significant (as well as the total heterogeneity), because this indicates that the variance of the mean effect might be stabilized if the studies could be partitioned further within the categories.

Mixed-Effects Model With Hedges' *d*

Hedges' *d* may be sensitive to the amount of variation that is incorporated into the mixed-effects model.

The mixed-effects model using Hedges' *d* yields significant effects for each individual fuel size class (fig. 2). Interestingly, the effect size of each time-lag class is larger than it was in the fixed- effects model. This suggests that Hedges' *d* may be sensitive to the amount of variation that is incorporated into the mixed-effects model, and unassigned in the fixed-effects model, just as it is sensitive to the standard deviation of the samples. In the case of the mixed-effects model, only Q_T and Q_B are available as measures of homogeneity because of the underlying assumption that there is significant heterogeneity within the model caused by random effects (Gurevitch and Hedges 2001).

The between-study heterogeneity (Q_B = 7.841, P (X^2) = 0.098) is not significant, indicating that the effect of prescribed fire is homogeneous at the level of fuel-size class and that comparisons between their effect sizes are not relevant. However, the total heterogeneity (Q_T = 118.48, P (X^2) < 0.001) is significant, presumably from

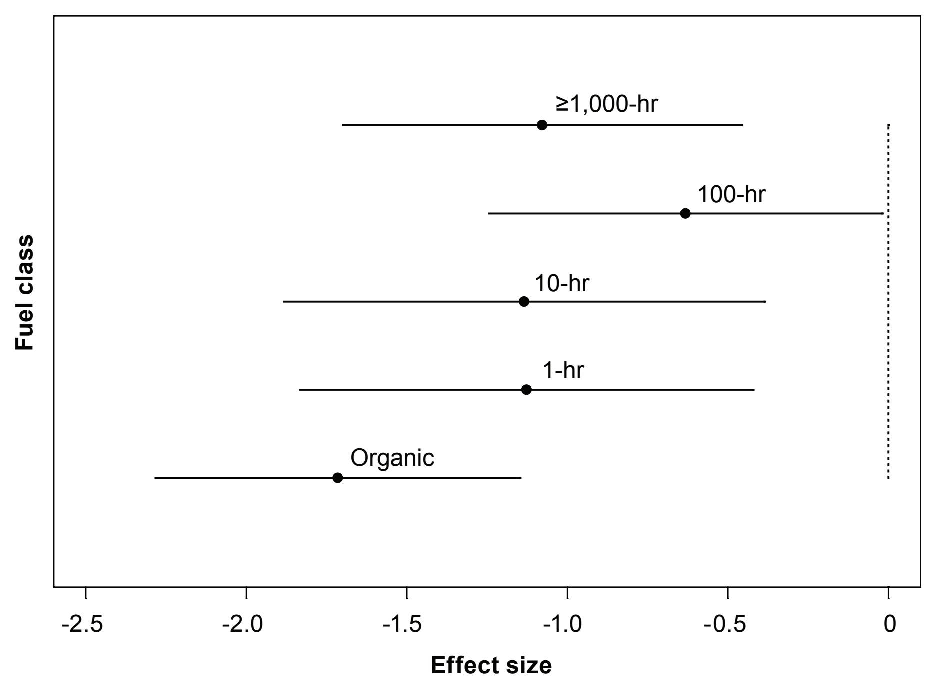

Figure 2—Mixed-effects model using Hedges' *d* as the metric of effect size with 95-percent confidence interval. Total heterogeneity Q_T = 118.48 (P(X^2) < 0.001) is significant; however, between-class heterogeneity Q_B = 7.841, (P(X^2) = 0.098) is not.

random variation in the effects of prescribed fire across the range of ecosystems represented in the meta-analysis. Although the total heterogeneity expressed in the mixed-effects model is noticeably smaller than that of the fixed-effects model, without significant between-class heterogeneity the analysis is terminated rather than being partitioned further (e.g., into fire season or sound vs. rotten wood as in the fixed-effects model).

Fixed-Effects Model With Log Response Ratio

The *ln*R effect sizes of the fuel classes are all significant (fig. 3), and the homogeneity test expresses significant heterogeneity between the fuel classes (Q_B = 29.63, P (X^2) < 0.001). The 100-hr time-lag class still has the smallest mean effect size, but the ranking of the effect sizes of the other fuels classes has changed. Notably, the organic and 10-hr fuel classes are in opposite positions relative to the fixed-effects model with Hedges' *d*; organic fuel has the second smallest mean effect size, and the 10-hr fuel class has the largest mean effect size, although it is not as large as the organic effect size is in the first model. These results are less conclusive than those of the first model owing to the larger amount of within-class heterogeneity.

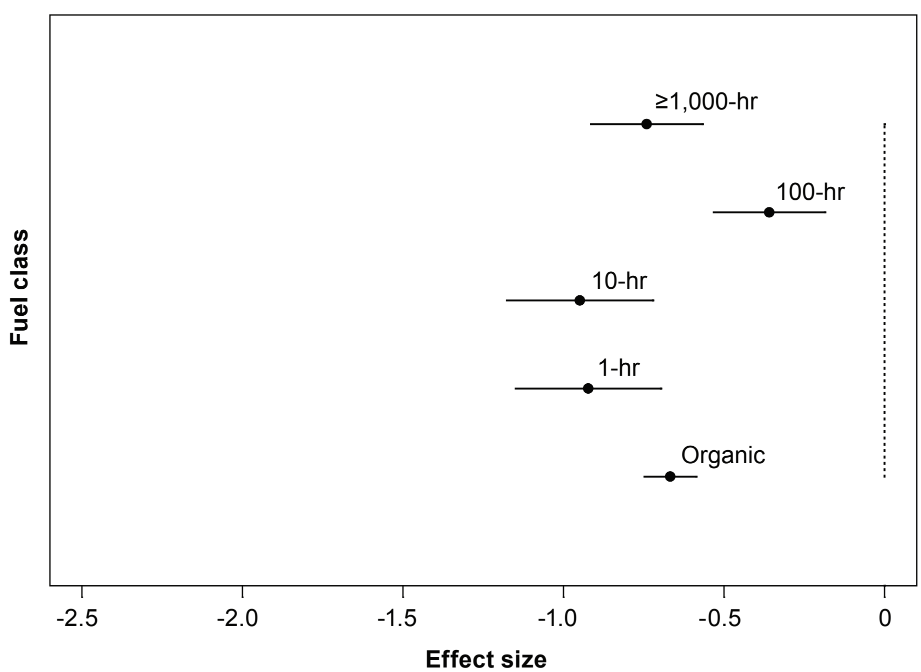

Figure 3—Fixed-effects model using the log response ratio lnR as the metric of effect size with 95-percent confidence interval. Total heterogeneity Q_T = 785.96 (P(X^2) < 0.001), between-class heterogeneity Q_B = 29.63 (P(X^2) < 0.001), and within-class heterogeneity Q_W = 756.32 (P(X^2) < 0.001) are all significant.

Significant heterogeneity within the fuel classes (Q_W = 756.32, P (X^2) < 0.001) suggests that the classes could be broken down into smaller groups. Therefore, the ≥1,000-hr fuel classes were partitioned into solid and rotten components as in the fixed-effects model using Hedges' *d* (table 4). Unlike the Hedges' *d* model, both between-class heterogeneity and within-class heterogeneity of individual effect sizes were significant. In this case, categorical analysis within the solid and rotten fuel classes is inconclusive because further partitioning is justified, but the sample sizes would have become too small.

A categorical analysis of seasonal effects on fuel reduction (table 5), using the fixed-effects model with *ln*R, was executed in the same manner as with Hedges' *d*. In contrast to the Hedges' *d* analysis, in which most of the results were terminated, the *ln*R results are inconclusive for all but the 100-hr fuel class.

Table 4—Heterogeneity tests and mean effect sizes using a fixed-effects model with the log response ratio *ln*R to partition the >1,000-hr fuel class into categories of solid (1,000s) and rotten (1,000r)

	Heterogeneity		
Model	**df**	**Q**	**P X^2**
Between	1	4.71	0.030
Within	17	71.82	< 0.001
Total	18	76.53	< 0.001

	Mean effect size			
Size class	**N**	***E***	**df**	**95% CI**
1,000s	10	-0.27	9	-0.53 to -0.01
1,000r	9	-0.81	8	-1.31 to -0.30
Total	19	-0.39	17	-0.60 to -0.17

Table 5—Summary results of heterogeneity tests using the fixed-effects model with *ln*R for the categorical analysis of burning season (spring versus fall) on fuel reduction

	Heterogeneity tests			
Fuel class	**Between**	**Within**	**Total**	**Result**[a]
Organic	40.52 P(X^2) < 0.001	305.13 P(X^2) < 0.001	345.64 P(X^2) < 0.001	Inconclusive
1-hr	19.48 P(X^2) < 0.001	130.36 P(X^2) < 0.001	149.84 P(X^2) < 0.001	Inconclusive
10-hr	4.86 P(X^2) = 0.028	89.05 P(X^2) < 0.001	93.90 P(X^2) < 0.001	Inconclusive
100-hr	0.47 P(X^2) = 0.495	90.95 P(X^2) < 0.001	91.42 P(X^2) < 0.001	Terminated
≥1,000-hr	4.33 P(X^2) = 0.038	71.19 P(X^2) < 0.001	75.52 P(X^2) < 0.001	Inconclusive

[a] See text for explanations of "inconclusive" and "terminated."

Mixed-Effects Model With Log Response Ratio

To examine sensitivity to the assumptions of a fixed-effects model, we fit mixed-effects models with *ln*R (fig. 4). When random effects are incorporated into the analysis through the use of the mixed-effects model, between-class heterogeneity and total heterogeneity are not significant (Q_B = 2.07, P (X^2) = 0.722; and Q_T = 74.93, P (X^2) = 0.211, respectively).

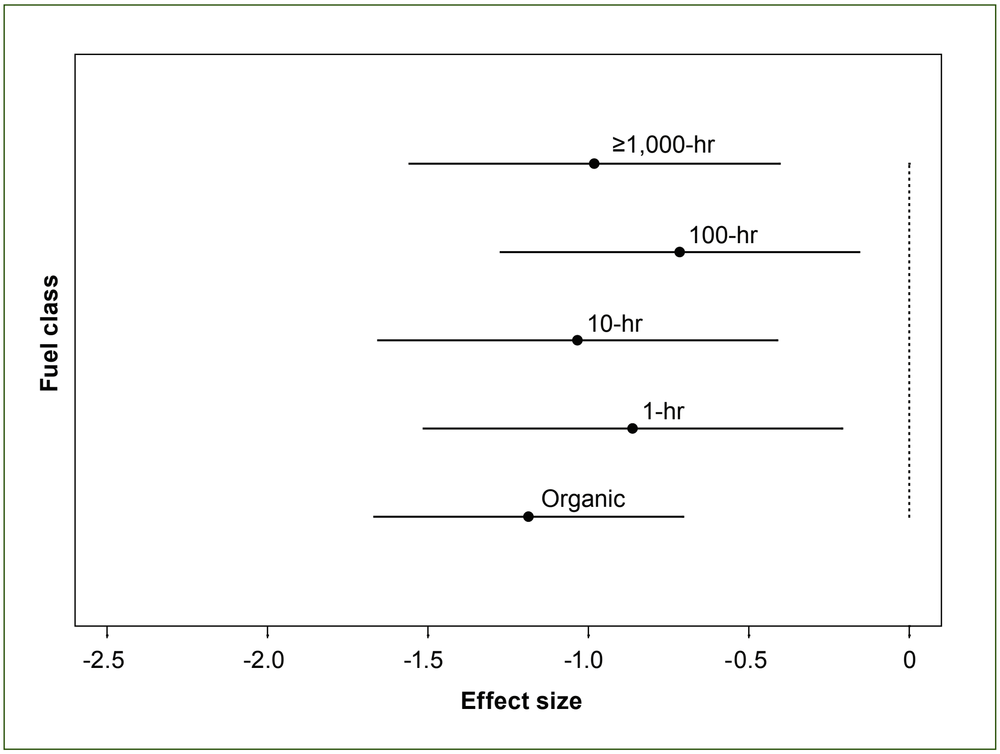

Figure 4—Mixed-effects model using the log response ratio lnR as the metric of effect size with 95-percent confidence interval. Total heterogeneity Q_T = 74.93 (P(X^2) = 0.211) and between-class heterogeneity Q_B = 2.07 (P(X^2) = 0.722) are not significant.

The confidence intervals around the mean effect of each fuel class do not include zero, which confirms the significance of these effect-sizes, although the confidence intervals have increased substantially over those from the fixed-effects model. The changes in the mean effect sizes using the mixed-effects model rather than the fixed-effects model (table 6) suggest that the explicit incorporation of random effects has a significant effect on results. The mixed-effects model increased the estimated effect size of the 100-hour fuels markedly, such that it is no longer clearly smaller than the effect sizes of the other fuel classes. There would be little profit in comparing effect sizes among the individual size classes given the increased confidence intervals around them.

The confidence intervals have increased substantially over those from the fixed-effects model.

Table 6—Mean effect size *E* for each time-lag fuel class using the mixed-effects model with *ln*R

Fuel class	N	E	df	95% CI
Organic	19	-1.19	18	-1.67 to -0.71
1-hr	11	-0.86	10	-1.51 to -0.21
10-hr	11	-1.03	10	-1.66 to -0.41
100-hr	13	-0.72	12	-1.27 to -0.16
>1,000-hr	13	-0.98	12	-1.56 to -0.41

Discussion

Meta-analysis has the potential to be a powerful tool for both scientists and managers. The results of our meta-analyses verify that fuel consumption was significant, and provide the mean quantity of fuels reduced per fuel time-lag class. These effect sizes, if they pertained to a set of fires prescribed for fuel reduction, would enable fire managers to evaluate whether objectives were met, and to document their effectiveness. Meta-analyses of this type of fire data can also serve as a means of comparing heterogeneous treatments or fire effects on individual time-lag classes.

Meta-analysis is relatively new to natural resources. A better understanding is needed regarding the pitfalls in the process when applied to ecological data. The mixed-effects model incorporates random variation, thus making it intuitively appealing for ecological applications, wherein systems are known to be heterogeneous (Gurevitch and Hedges 1999). It does have its drawbacks, however. The mixed-effects model successfully stabilized variance by characterizing the response among “categories” (heterogeneous groups) as a random variable, but in doing so, bypassed the iterative process of “categorical” meta-analysis that may be superior when prior ecological knowledge informs the choice of categories. As discussed previously, it is the categorical analysis that allows the investigator to identify other environmental factors that may be directly associated with ecological mechanisms. The lack of significant heterogeneity between the classes also precludes their comparison, which can be a useful tool to explore treatment effects as shown in the fixed-effects analyses.

On the other hand, it could be misleading to ignore sources of random variation that are clearly present, because one could come away with a false sense of significance. The large confidence intervals around the mean effect sizes of individual fuel time-lag classes in the mixed-effects *ln*R model belie the apparent significance of differences among prescribed fire effects on individual classes. It is probable that the failure to detect significant differences is due to inherent random variation in true effect size among sites, a factor identifiable only with the mixed-effects model.

Despite the random component inherent in biological systems, it is important to identify all of the potential sources of variation (e.g., season, forest type, treatment) within the bounds of the meta-analysis and partition accordingly. Two or more replicates are required to test each variable that is identified. Although the categorical analyses of the fixed-effects models were executed to the point where further analysis was not possible, it is not clear if the inclusion of studies with more ecological variability, such as forest types other than ponderosa pine, might have increased the sample size enough to overcome the drawbacks of new sources of random variation.

Meta-analysis provides distinct advantages over ANOVA for studies with heterogeneous sampling designs, such as those from literature reviews. Simple ANOVA is not appropriate for combining the results of individual studies, because it will almost surely violate the assumption of equal variances across sites. Like simple ANOVA, the categorical meta-analysis partitions the variance of the effect, but it is not prone to Type 2 errors if the constraints of homogeneous sample sizes and variances are not met (Hedges and Olkin 1985).

The problem of heterogeneous variance by itself does not have to be resolved by using meta-analysis. The data analyst may incorporate an explicit model of variance, at least in a mixed-effects model (Davidian and Giltinan 1995, Pinheiro and Bates 2000). If the mixed-effects approach is selected a priori, then explicit variance modeling can be analogous to meta-analysis, although the methodology of the former is less intuitive and the mathematical details are more daunting.

The generally equivalent results illustrate the robustness of the meta-analytic paradigm to the choice of statistical details.

We explored four alternative approaches to meta-analysis of heterogeneous ecological data. The generally equivalent results (figs. 1 through 4) illustrate the robustness of the meta-analytic paradigm to the choice of statistical details. Each outcome confirms that prescribed fire significantly reduces fuels, although the different models do not agree on the relative rankings of mean effect sizes for different fuel categories. It would be premature to conclude, based on the outcome of this study, that one of the four methods is superior. (Indeed, a favorable outcome of just one approach could be misleading). Instead, we suggest that subject-matter considerations, where possible, should drive the choice of models and metrics of effect size.

Osenberg et al. (1999) showed how meta-analysis can be adapted to a variety of effect-size metrics, some quite complex nonlinear functions of observed variables. In cases where results may be less robust than ours to such choices, considerable care should be taken to identify a model that is ecologically interpretable. In our case, the effect sizes from both metrics increased slightly when the fixed-effects model was replaced with the mixed-effects model, suggesting that both metrics are sensitive to variation in the model, and neither is clearly superior.

Some inconclusive results in the fixed-effects models (mainly in the analyses using *ln*R), when what appeared to be essential divisions of data into season of burning and sound versus rotten fuels halted the iterative meta-analysis procedure, indicate the advantages of planning meta-analyses before data collection, as opposed to meta-analyses derived from literature reviews. In planning a meta-analysis of fire effects, the researcher would have control over measurement techniques and sample sizes. Furthermore, potential response variables are not limited to those identified in literature reviews. Broad-scale experiments such as the fire and fire surrogates (FFS) study (McIver et al. 2009) provide an opportunity to extend our results using more homogeneous (controlled) data with greater replication (Waldrop et al. 2004). The large sample size and planned design of the FFS study make it well suited to categorical meta-analyses of variables such as seasonality, regional patterns, and environmental and ecological differences between sites. Meta-analyses from planned studies can also prevent pseudoreplication, and other issues involving dependent data that can arise from the use of unfamiliar and inconsistent summary statistics.

More generally, standardized methodology and collaborative efforts in fire research and other areas of natural resource science will lead to more robust synthesis and interpretation across study sites. Fire science topics for which meta-analysis may be particularly effective include comparisons of timing, fire intensity, and fuel moisture on tree mortality or vegetative response. This fire information is typically documented in association with prescribed and wildland fires regardless of landowner, and these response variables are often monitored in association with prescribed fire, or can be evaluated postfire. In the broader context of natural resource management, meta-analysis is applicable to inventories and monitoring projects such as wildlife surveys, restoration planting survivorship, and other projects in which there is a large quantity of data collected.

Individual authors can facilitate the performance of meta-analyses by reporting both significant and insignificant results to avoid journalism bias (and editors could be more receptive to the latter), and by providing all summary statistics in published reports. To expedite the synthesis of large data sets in natural resources, we emphasize the need for collaboration between researchers and resource managers in the development and use of multiagency storage sites for metadata and summaries. Examples of these types of databases include FIREHouse (USDA Forest Service et al. 2006) and the National Biological Information Infrastructure (U.S. Geological Survey 2006).

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Appendix

Table 7—Summary of the fuel-treatment data sets used in the meta-analysis

Source of study	State	Burn	Site	Fuel class[a]	n[b]	Control Mean fuel load	Control Standard deviation	Treatment Mean fuel load	Treatment Standard deviation
Busse et al. (2000)	Oregon	Spring 1988	Fremont	100-hr	14	6.40	2.99	5.20	2.62
				1,000-hr	14	26.40	16.46	1.20	17.39
				Organic	14	21.70	10.85	16.60	10.10
Davis et al. (1964)	Arizona	Fall 1964	Beavercreek	Organic	2	2.35	2.21	0.66	2.43
Kalabokidis and Wakimoto (1992)	Montana	Fall 1982	Champion	1-hr	30	0.22	0.14	0.06	0.06
				10-hr	30	2.16	2.14	1.96	2.01
				100-hr	30	2.54	2.85	1.70	1.65
				1,000-hr	30	3.39	5.75	1.24	2.93
				Duff	30	4.73	3.45	3.59	3.07
				Litter	30	4.60	3.61	1.29	1.73
				Organic	30	9.33	3.53	4.88	2.49
			Lubrecht	1-hr	30	0.46	0.28	0.16	0.17
				10-hr	30	2.73	2.12	1.54	1.73
				100-hr	30	3.67	2.45	3.82	3.55
				1,000-hr	30	6.49	10.13	0.82	1.27
				Duff	30	18.56	6.40	13.56	11.52
				Litter	30	4.67	5.39	1.89	2.52
				Organic	30	23.23	5.92	15.45	8.34
Kauffman and Martin (1989)	California	Fall 1984	Blodgett (a)	1-hr	5	0.30	0.22	0.20	0.00
				10-hr	5	5.70	1.79	0.70	0.67
				100-hr	5	4.00	1.79	0.70	0.45
				1,000s	5	9.90	3.13	5.90	2.91
				1,000r	5	14.00	12.97	0.50	0.89
				1,000	5	23.90	9.43	6.40	2.15
				Organic	5	118.10	20.35	7.70	2.91
			Blodgett (b)	1-hr	5	0.20	0.22	0.10	0.22
				10-hr	5	4.00	2.68	3.50	2.91
				100-hr	5	2.50	1.34	2.70	1.57
				1,000s	5	56.70	29.74	5.00	4.25
				1,000r	5	7.90	12.75	7.60	10.96
				1,000-hr	5	64.60	22.88	12.60	8.31
				Organic	5	105.80	23.26	37.80	8.72
		Spring 1984	Blodgett (c)	1-hr	5	0.70	0.67	0.10	0.22
				10-hr	5	6.00	2.91	2.50	1.34
				100-hr	5	6.10	6.04	4.60	3.80
				1,000s	5	33.10	33.32	20.80	28.18
				1,000r	5	11.30	20.13	15.00	20.35
				1,000-hr	5	44.40	27.52	35.80	24.58
				Organic	5	97.50	5.37	86.40	10.73
			Blodgett (d)	1-hr	5	0.70	0.67	0.10	0.00
				10-hr	5	4.70	1.79	0.80	0.67
				100-hr	5	1.80	1.12	1.00	0.67
				1,000s	5	9.30	8.05	17.50	10.06
				1,000r	5	31.10	44.50	11.60	22.58
				1,000	5	40.40	31.47	29.10	17.48
				Organic	5	83.30	8.50	20.10	9.84

Table 7—Summary of the fuel-treatment data sets used in the meta-analysis (continued)

						Control		Treatment	
Source of study	State	Burn	Site	Fuel class[a]	n[b]	Mean fuel load	Standard deviation	Mean fuel load	Standard deviation
		Fall 1984	Challenge (a)	1-hr	5	0.90	0.45	0.20	0.22
				10-hr	5	4.70	1.79	0.50	0.22
				100-hr	5	6.30	2.46	1.00	0.67
				1,000s	5	19.20	15.21	4.10	3.80
				1,000r	5	7.70	7.16	0.00	0.00
				1,000-hr	5	26.90	11.88	4.10	2.69
				Organic	5	118.30	29.07	7.10	15.88
			Challenge (b)	1-hr	5	0.80	0.22	0.20	0.22
				10-hr	5	3.40	1.79	1.20	1.12
				100-hr	5	3.80	2.46	2.50	2.01
				1,000s	5	10.70	9.39	8.90	4.47
				1,000r	5	6.20	4.92	0.80	1.79
				1,000-hr	5	16.90	7.50	9.70	3.41
				Organic	5	125.80	23.93	20.00	8.27
		Spring 1984	Challenge (c)	1-hr	5	1.10	0.45	0.40	0.22
				10-hr	5	4.50	2.68	2.20	0.67
				100-hr	5	3.70	1.34	2.50	2.68
				1,000s	5	4.80	2.68	6.50	9.62
				1,000r	5	7.20	11.63	9.70	18.78
				1,000-hr	5	12.00	8.44	16.20	14.92
				Organic	5	103.90	14.31	30.90	9.17
			Challenge (d)	1-hr	5	0.70	0.45	0.10	0.00
				10-hr	5	4.40	0.22	0.20	0.22
				100-hr	5	4.00	4.03	0.30	0.22
				1,000s	5	22.20	14.31	13.40	8.72
				1,000r	5	12.60	9.17	4.70	7.83
				1,000-hr	5	34.80	12.02	18.10	8.29
				Organic	5	120.70	35.78	9.50	4.92
Kovacic et al. (1986)	New Mexico	Winter 1981	Jemez Springs (a)	Organic	5	0.35	1.07	0.20	1.12
			Jemez Springs (b)	Organic	5	0.38	1.07	0.11	1.12
			Jemez Springs (c)	Organic	5	0.41	1.05	0.18	1.01
Landsberg et al. (1984)	Oregon	Spring 1979	Deschutes (a)	Organic	2	2.50	0.70	1.28	0.36
			Deschutes (b)	Organic	2	3.90	1.60	0.47	0.19
Sackett and Haase (1998)	Arizona	Fall 1976	Chimney	100-hr	3	1.82	0.51	2.58	1.61
				1,000s	3	4.68	3.18	5.94	1.87
				1,000r	3	9.55	9.26	6.19	4.18
				1,000-hr	3	14.23	6.92	12.13	3.24
		Fall 1977	Limestone	1-hr	3	1.08	0.54	24.17	9.38
				10-hr	3	4.73	3.09	12.71	2.29
				100-hr	3	4.91	1.46	0.83	0.44
				1,000s	3	11.70	10.34	4.01	3.17
				1,000r	3	20.51	9.19	0.09	0.19
				1,000-hr	3	32.21	9.78	4.10	2.25
				Organic	18	24.86	2.56	14.72	5.25
Sweeney and Biswell (1961)	California	Spring 1959	Lake County	Organic	4	11.17	11.54	6.89	4.26

[1] Fuel variables are described in the text.
[2] n = number of replicates, same for the treatment (postburn) and control (preburn) groups.
[3] The fuel load units vary by source, and are not reported here because the effect size metric is a unitless measure.

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Pacific Northwest Research Station
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