

Assessing accuracy of point fire intervals across landscapes with simulation modelling

Russell A. Parsons, Emily K. Heyerdahl, Robert E. Keane, Brigitte Dorner, and Joseph Fall

Abstract: We assessed accuracy in point fire intervals using a simulation model that sampled four spatially explicit simulated fire histories. These histories varied in fire frequency and size and were simulated on a flat landscape with two forest types (dry versus mesic). We used three sampling designs (random, systematic grids, and stratified). We assessed the sensitivity of estimates of Weibull median probability fire intervals (WMPI) to sampling design and to factors that degrade the fire scar record: failure of a tree to record a fire and loss of fire-scarred trees. Accuracy was affected by all of the factors investigated and generally varied with fire regime type. The maximum error was from degradation of the record, primarily because degradation reduced the number of intervals from which WMPI was estimated. The sampling designs were roughly equal in their ability to capture overall WMPI, regardless of fire regime, but the gridded design yielded more accurate estimates of spatial variation in WMPI. Accuracy in WMPI increased with increasing number of points sampled for all fire regimes and sampling designs, but the number of points needed to obtain accurate estimates was greater for fire regimes with complex spatial patterns of fire intervals than for those with relatively homogeneous patterns.

Résumé : Nous avons évalué l'exactitude des intervalles des feux à un point donné à l'aide d'un modèle de simulation qui a échantillonné quatre historiques simulés des feux spatialement explicites. Ces historiques variaient quant à la fréquence et la dimension des feux et ont été simulés dans un paysage plat avec deux types de forêt (sèche versus mésique). Nous avons utilisé trois plans d'échantillonnage (aléatoire, grille systématique et stratifié). Nous avons évalué la sensibilité des estimations de la médiane de Weibull des intervalles des feux à un point donné (MWIF) au plan d'échantillonnage et aux facteurs qui causent la détérioration des données de cicatrices de feu : un arbre qui n'est pas marqué par le feu ou la perte d'arbres portant une cicatrice de feu. L'exactitude était affectée par tous les facteurs qui ont été étudiés et variait généralement selon le type de régime des feux. L'erreur maximum provenait de la dégradation des données, principalement parce que la dégradation réduisait le nombre d'intervalles à partir desquels la MWIF était estimée. Les plans d'échantillonnage étaient à peu près équivalents quant à leur capacité à capturer la MWIF globale, peu importe le régime des feux, mais le plan en damier a produit des estimations plus exactes de la variation spatiale de la MWIF. L'exactitude de la MWIF augmentait avec le nombre de points échantillonnés pour tous les régimes des feux et tous les plans d'échantillonnage mais le nombre de points nécessaires pour obtenir des estimations exactes était plus élevé pour les régimes des feux avec des patrons complexes d'intervalles des feux que pour ceux dont le patron était relativement homogène.

[Traduit par la Rédaction]

Introduction

In North America, estimates of historical fire frequency are increasingly used to guide management of natural resources, such as landscape-scale forest restoration and fuel treatment (Wildland Fire Research Council 2006). However, uncertainty in these estimates can reduce the scientific impact of fire history reconstructions and erode their utility to management. Historical fire frequency can be reconstructed from a variety of proxy records, for example, the establishment dates of postfire cohorts of trees (Reed 1994; Reed et al. 1997) and charcoal found in lake sediments (Cwynar 1987; Clark 1990), but here we focus on fire frequency reconstructed from fire scars on trees (Dieterich and Swetnam

1984). While estimating fire frequency from these scars is straightforward, the *accuracy* of such estimates depends on the completeness of the fire scar record and a sampling design that adequately captures that record. The magnitude of errors introduced by both of these sources is likely to depend on the homogeneity of fire regimes across the area being sampled. The fire scar record may not be complete because it can be degraded by natural processes that render it patchy in time and space. For example, a tree may not develop a scar from all of the fires that burn near it and fire scars can be lost over time as fire-scarred trees and individual fire scars are consumed by subsequent fires or rot (Van Pelt and Swetnam 1990). Fire history sampling has been the subject of much recent debate (Johnson and Gutsell 1994;

Received 19 May 2006. Accepted 18 January 2007. Published on the NRC Research Press Web site at cjfr.nrc.ca on 21 September 2007.

R.A. Parsons,¹ E.K. Heyerdahl, and R.E. Keane. USDA Forest Service, Rocky Mountain Research Station, Fire Sciences Laboratory, 5775 West Highway 10, Missoula, MT 59808, USA.

B. Dorner. School of Resource and Environmental Management, Simon Fraser University, Burnaby, BC V5A 1S6, Canada.

J. Fall. School of Computing Science, Capilano College, 2055 Purcell Way, North Vancouver, BC V7J 3H5, Canada.

¹Corresponding author (e-mail: rparsons@fs.fed.us).

Fall 1998; Baker and Ehle 2001; Fulé et al. 2003; Reed and Johnson 2004; Van Horne and Fulé 2006), but in general, errors inherent in the record available for sampling have been ignored in fire history studies. Accuracy in estimates of fire frequency can only be evaluated if the true fire frequency is known, which is never the case in field studies, and direct comparison of different sampling designs in the same location is generally impractical due to the time and effort needed to process fire scars (Weisburg and Swanson 2001; but see Van Horne and Fulé 2006). However, spatially explicit simulation models can be used to generate simulated fire histories, which can be degraded and sampled to mimic field studies (Li 2002; Fall 1998; Lertzman et al. 1998) and thus help to identify the relative contributions of patchiness in the fire scar record, sampling design, and fire regime to errors in estimates of fire frequency. This information may lead to changes in the design of fire history studies that reduce such errors.

Historical fire frequency is often quantified as fire intervals, or the time between successive fires (Merrill and Alexander 1987). To compute these intervals, physical samples containing scars are collected (Arno and Sneek 1977) and can be cross-dated to assign the correct calendar year to each fire scar (Dieterich 1980). Because a tree may not be scarred by every fire that burns near it (Vines 1968; Romme 1980; Dieterich and Swetnam 1984; Fall 1998; Baker and Ehle 2001), fire scar dates from nearby trees (e.g., within 1 ha) are often pooled to compute a composite point fire interval that is assumed to be more complete than intervals computed from individual trees (Dieterich 1980). These composite point fire intervals are often characterized by their mean (Arno and Sneek 1977; Kilgore and Taylor 1979), but fire interval distributions are often positively skewed, so instead a statistical distribution, such as the Weibull, is fit to the distribution of intervals (Johnson 1979; Johnson and Van Wagner 1985; Baker 1989; Grissino-Mayer 1999; Polakow and Dunne 1999). The median of this distribution, or Weibull median probability interval (WMPI) (Grissino-Mayer 1999), is a measure of central tendency that is robust to positively skewed distributions and is often used to characterize fire frequency (Grissino-Mayer 1999; Polakow and Dunne 1999).

Our objective was to assess the accuracy (i.e., relative magnitude of errors) in estimates of point fire intervals as a function of (1) the number of intervals used in the estimate, (2) the fire regime being sampled (i.e., fire frequency and size), (3) sampling design and intensity, and (4) degradation of the fire scar record resulting from failure of a tree to record a fire and from the loss of fire-scarred trees over time to rot or subsequent fires. We accomplished objective 1 by performing a bootstrap analysis of fire intervals computed from fire scars at five real plots (1–3 ha), objective 2 by generating four simulated fire histories from four different fire regimes, and objectives 3 and 4 by sampling or degrading those fire histories (Fig. 1; Table 1).

Methods

Analysis 1: Effect of the number of fire intervals

To assess the sensitivity of estimates of median point fire intervals to the number of intervals used to compute that estimate, we used observed fire intervals from five points at which a range of number of intervals had been reconstructed

from fire scars (6–44 intervals) and determined the margin of error with bootstrapping (Fig. 2). The fire intervals at each point were composited from trees collected over 1–3 ha (BCW plot 5, DCR plot 13, and IRC plot 2, Heyerdahl et al. 2001; AJT, Heyerdahl and Alvarado 2003; BGH plot 6D, Heyerdahl et al. 2006). We fit a Weibull distribution (Grissino-Mayer 1999) to the composite record of intervals from each plot (Dieterich 1980) and generated 50 synthetic lists of 80 fire intervals each using the Weibull parameters determined for that plot. We applied a nonparametric bootstrap to each synthetic list (1000 samples) to estimate the margin of error for the estimated median interval calculated as (Higgins 2004)

$$[1] \quad \text{Merr} = 2\sqrt{\text{MSE}}$$

incrementally removing an interval from the record and repeating this process until we reached five intervals. We iterated the random removal of intervals five times at each level. The 50 replicates of the synthetic lists, as well as multiple instances of interval removal, served to eliminate artifacts that might have arisen as an effect of any particular random draw. We used nonlinear fitting procedures to fit power functions to the mean margin of error, averaged across all synthetic lists, as a function of the number of intervals (SAS Institute Inc. 1989). For this analysis, we used the median as a nonparametric measure rather than the WMPI to eliminate the need for another fitting routine within this bootstrap procedure and because the median and WMPI were nearly identical.

Analysis 2: Simulated fire histories

We developed a simple stochastic simulation model to generate four simulated fire histories, one each from four different fire regime types (Table 2). The simulation landscape was flat and square with no barriers to fire spread. To reduce edge effects (Keane et al. 2002), we ran initial simulations on a landscape (64 × 64, 1 ha cells, total area 4096 ha) but used only the central portion (50 × 50, 1 ha cells, total area 2500 ha) in subsequent analyses. The landscape included coarse-scale heterogeneity in forest type (half dry forest and half mesic) arranged in a random aggregated pattern (Fig. 3a). Fires were more likely to occur and be patchy in dry forest (probabilities 0.7 and 0.95, respectively) than in mesic forest (probabilities 0.3 and 0.65, respectively). Dry forest cells were thus more than twice as likely to be the location of a fire start and burned more consistently across cells than those in mesic forest. However, fires were homogeneous within each 1 ha cell.

We simulated fires with two independent Weibull probability distribution functions, one for fire occurrence and one for fire size. Over the simulation (4000 one-year time steps), the interval between successive fires was drawn from the first distribution, and a circular fire, with size drawn from the second distribution, was placed on the landscape. The center cell of each fire was determined randomly but constrained by the probability of fire start location by forest type. The Weibull distributions were defined by their scale (b) and shape parameters (c):

$$[2] \quad W_{(b,c)} = b(-\log(R))^{(1/c)}$$

where R is a random number drawn from the uniform distri-

Fig. 1. Overview of study design and simulation modelling used to assess the accuracy of estimates of the Weibull median probability interval (WMPI) reconstructed from fire scars.

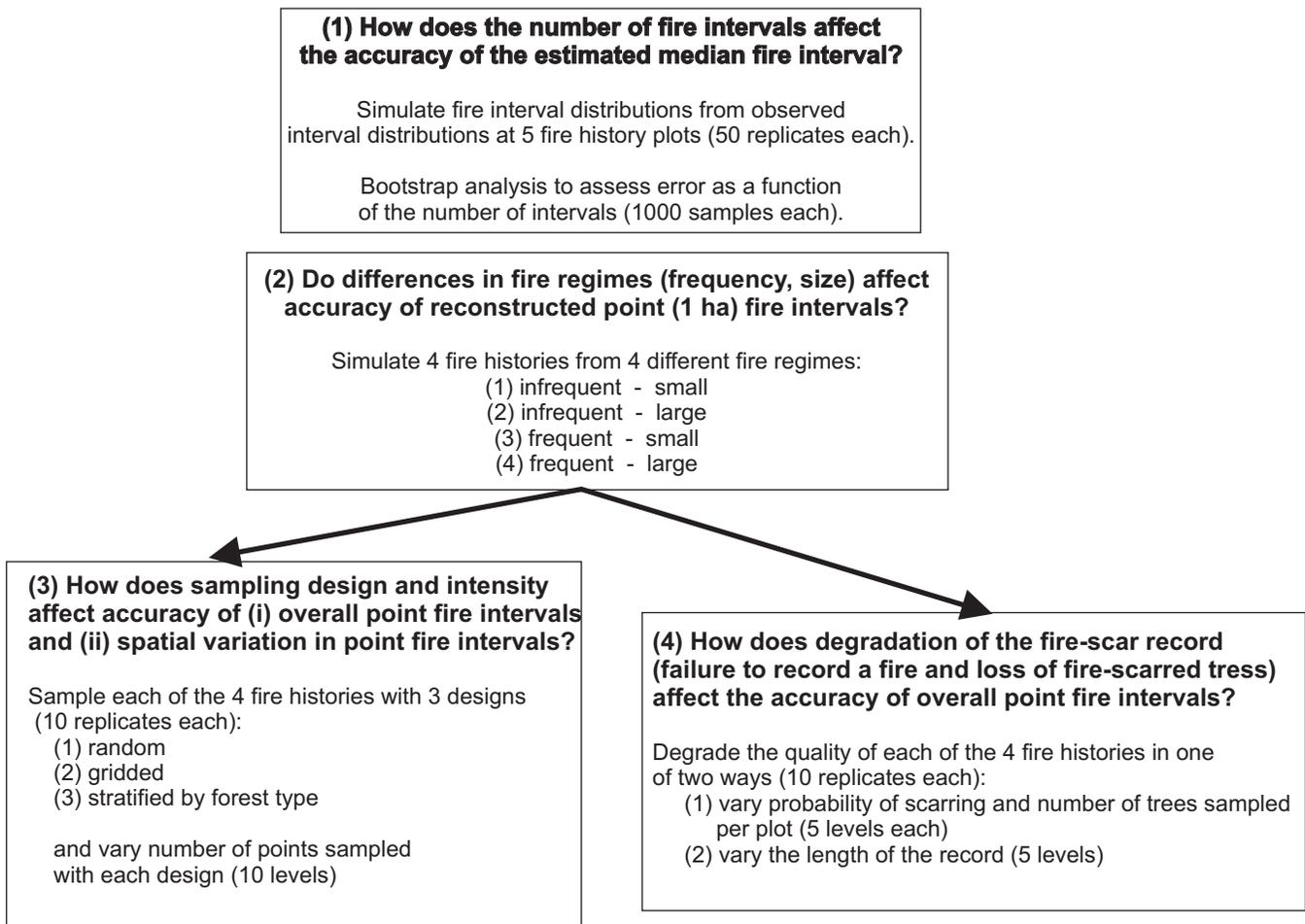


Table 1. Summary of analyses 1, 3, and 4 (Fig. 1).

Factors (number of levels)	Levels
Analysis 1: Number of intervals used in calculation of median (5 fire history plots)	
Synthetic lists of intervals	50 lists for each plot
Bootstrap samples	1000 samples
Replicates of interval removal	5 iterations at each number of intervals
Number of fire intervals (76)	5–80 intervals in increments of 1
Analysis 3: Sampling design and intensity (10 replicates each)	
Fire regime (4)	Infrequent–small, infrequent–large, frequent–small, frequent–large
Sample design (3)	GRID, RANDOM, or STRATA
Sampling intensity (10)	16, 25, 36, 49, 64, 81, 100, 144, 196, or 256 points
Analysis 4: Degradation of the fire-scar record (10 replicates each)	
Fire regime (4)	Infrequent–small, infrequent–large, frequent–small, frequent–large
Probability of scarring (5)	0.1, 0.3, 0.5, 0.7, or 0.9
Number trees sampled per point (5)	1, 2, 3, 4, or 5
Length of record, shape parameter (4)	1, 2, 3, or 4
Length of record, scale parameter (9)	100–500 in increments of 50

Note: Analysis 2, the development of the synthetic fire regimes, is described in Table 2.

bution (Evans et al. 1993). The shape parameter describes the nature of the variability in the distribution. We assumed a constant flammability over time and thus held the shape parameter for fire occurrence constant at 1. In this form,

the Weibull distribution is equivalent to the negative exponential distribution (Johnson and Gutsell 1994, Van Wagner 1978) and has the convenient property that the mean of the distribution is equal to the scale parameter. The shape para-

Table 2. Summary of parameters and assumptions used in analysis 2 to simulate four fire histories from four different fire regimes (combinations of infrequent/frequent and small/large) with a simple spatial fire regime model.

Fire regime	Fire controls for simulation parameters							
	External to landscape				Internal by vegetation type			
	Fire occurrence (years)		Fire size (ha)		Dry forest		Mesic forest	
	Shape	Scale	Shape	Scale	<i>P</i> start	<i>P</i> burn	<i>P</i> start	<i>P</i> burn
Infrequent–small	1	10	1.5	250	0.7	0.95	0.3	0.65
Infrequent–large	1	10	1.5	250	0.7	0.95	0.3	0.65
Frequent–small	1	5	1.5	500	0.7	0.95	0.3	0.65
Frequent–large	1	5	1.5	500	0.7	0.95	0.3	0.65

Fire: model assumptions
 No change in flammability over time
 Time between fires for landscape drawn from the Weibull distribution and independent of fire extent
 Fire is homogeneous within each 1 ha cell
 Fire shapes are circles, with size drawn from the Weibull distribution

Properties of simulation landscape
 Topography: flat
 Vegetation: equal proportions of dry and mesic forest
 Landscape area: 64 × 64, 100 m × 100 m (1 ha) cells, total area 4096 ha
 Analysis area: 50 × 50, 100 m × 100 m (1 ha) cells, total area 2500 ha

Note: *P* start and *P* burn are the probabilities of a fire igniting and burning, respectively.

meter for fire size was held constant at 1.5. We did not include any changes in fuel or forest state over time.

By holding the shape parameters constant for both probability distributions and by using the same landscape and associated parameters for all simulations, we reduced differences in fire regimes between simulated fire histories to two parameters: the scale parameter for fire occurrence and the scale parameter for fire size. We simulated four fire histories with different fire frequencies and sizes (Table 2): infrequent–small, infrequent–large, frequent–small, and frequent–large. Each fire history contains a record of point fire intervals for each of the 2500 one hectare cells in the simulation landscape. As a measure of how well the influence of differences in fire regimes by forest type was translated to each of the four fire histories that we simulated (i.e., smoothness in WMPI), we assessed a global measure of autocorrelation in point WMPI across the simulation landscape (isotropic Moran's *I* computed for adjacent cells, Goodchild 1986). Higher values of Moran's *I* indicate a smoother, more autocorrelated map (i.e., cells near one another have similar WMPI) than do lower values.

Analysis 3: Effect of sampling design and intensity

To assess the sensitivity of estimates of point fire intervals to sampling design, intensity, and fire regime type, we sampled each of our four simulated fire histories with three different sampling designs in which points (i.e., 1 ha cells and their corresponding fire interval records) were selected from the landscape using systematic grids (GRID), simple random sampling (RANDOM), or stratified random sampling by forest type (dry or mesic, STRATA). Each sampling design was applied with 10 different levels of sampling intensity (i.e., number of points sampled: 16, 25, 36, 49, 64, 81, 100, 144, 196, and 256 one hectare cells) with 10 replicates each (Fig. 1; Table 1). We assessed two measures of accuracy in point fire intervals estimated from

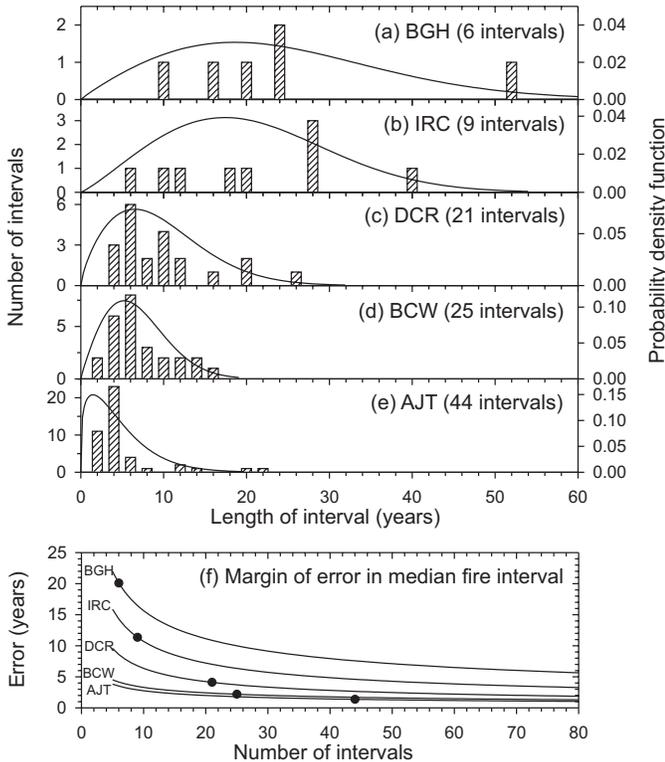
each combination of sampling design, intensity, and fire regime type: (i) overall WMPI and (ii) spatial variation in WMPI across the landscape. To assess the accuracy of the overall mean point fire interval, we computed the difference in WMPI of the overall distribution of point fire intervals (i.e., intervals computed in each 1 ha cell and pooled across the landscape) and WMPI from the distribution used to generate the fire history being assessed. We fit power functions to the distribution of errors from each combination of sampling design, intensity, and fire regime type and identified accurate estimates of WMPI as those that were within 10% of the true value. Although we recognize that different studies have different accuracy needs, we used 10% accuracy as a simple way of comparing results among our analyses.

To assess the sensitivity of estimates of the spatial variation in WMPI, we compared the maps of true WMPI with interpolated maps of WMPI at the sampled points. For each combination of sampling design, sampling intensity, and fire regime type, we fit splines to maps of WMPI at the 1 ha points sampled for that analysis (Figs. 3b and 3c; Sandwell 1987). Then for every 1 ha cell in the landscape, we computed the absolute difference between WMPI from the interpolated map and the reference WMPI and pooled these values across the landscape. We fit power functions to the distribution of mean absolute values of the difference in WMPI across all cells. This method of interpolating WMPI between sampled points has not been used widely in fire history studies but is well established in other fields. We used this approach because it enabled us to generate predictive surfaces given only values known at points, in this case, the WMPI value calculated from the fire intervals for that cell.

Analysis 4: Effect of degradation of the fire scar record

We assessed the sensitivity of estimates of point fire intervals to degradation of the fire scar record and fire regime

Fig. 2. (a–e) Distribution of observed fire intervals (bars in 2-year bins) and fitted distributions (lines) for five point fire history plots.



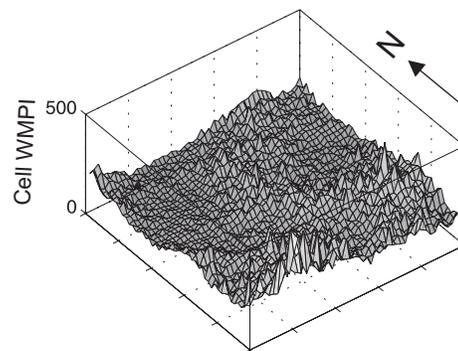
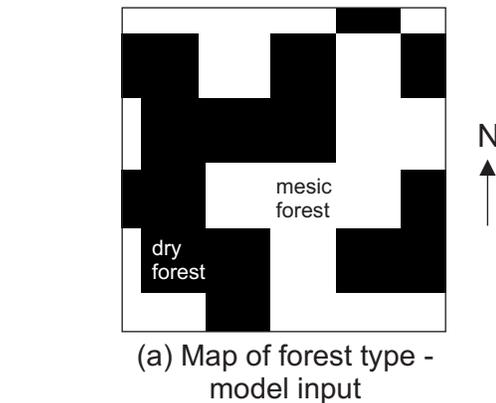
type in two separate analyses (Fig. 1; Table 1). First, for each of the four fire histories, we populated each 1 ha cell with a range of number of trees (one, two, three, four, or five trees). Each tree was initialized with the full record of fire years that had occurred in that cell and then separately subjected to a series of stochastic events designed to mimic failure to record a fire. We set the probability of each tree recording a fire at p (values from 0.1 to 0.9 with increments of 0.1, assumed to be a Poisson process) and the probability of failing to record a fire at $1 - p$. If a tree failed to record a fire, that individual scar was removed from the record for that tree. We did not consider misidentified or misdated fire scars, as both are generally avoidable (Weisburg and Swanson 2001). For each cell, we computed fire intervals from a composite of the degraded record of all trees in that cell. We pooled these fire intervals across the landscape and estimated an overall WMPI. We identified accurate estimates of the true WMPI as estimates from the degraded record that were within 10% of the true value.

Second, for each of the four fire histories, we modelled the loss of fire-scarred trees over time by treating the record of fire years in each cell as an independent record for which the earliest year was drawn from a Weibull survivorship function defined as

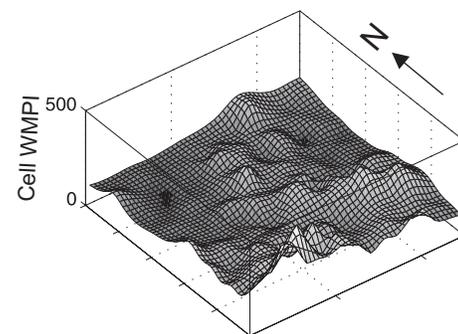
$$[3] \quad p(x) = e^{-(x/b)^c}$$

where x is a year, $p(x)$ is the probability of a tree's record extending x years back in time, and b and c are the Weibull scale and shape parameters, respectively. We used a range of shape (1–4, increment 1) and scale parameters (100–500, increment 50). We characterized the length of the record for

Fig. 3. Maps of model (a) input and (b and c) output. All maps include 2500 one hectare cells.



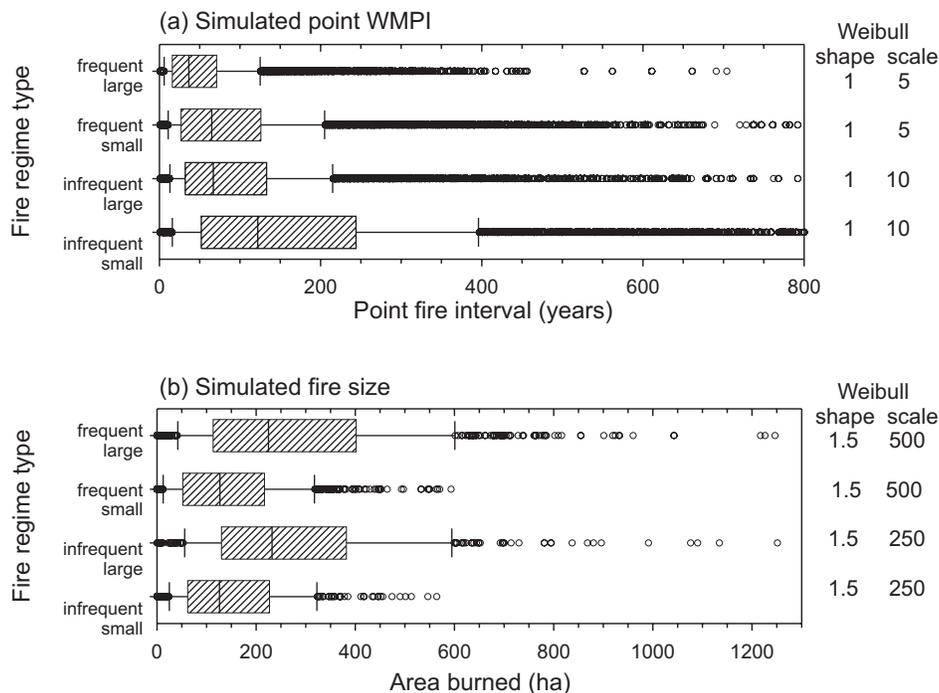
(b) Map of reference WMPI by cell for infrequent-small fire history - model output



(c) Interpolated map of WMPI by cell for frequent-large fire history sampled with 256 points - model output

each fire regime type as that length for which 80% of the cells have no fire intervals. This length varied from 160 to 800 simulation years. We pooled all the intervals remaining in the cells across the landscape for each combination of record length and fire regime type and computed the difference between this and the true WMPI. We identified accurate WMPIs as those that were within 10% of the true value. We have couched this form of degradation in terms of the loss of fire-scarred trees over time. However, it also mi-

Fig. 4. Properties of the four simulated fire histories from four different fire regimes (fire frequency and size) over the 4000 years of the simulation. Fire intervals were computed for each 1 ha cell and then pooled over the 2500 ha landscape. The boxes enclose the 25th to 75th percentiles of the distribution, the whiskers enclose the 10th to 90th percentiles, and the vertical line across each box indicates the 50th percentile. Circles mark all values lying outside the 10th to 90th percentiles, and all regimes but frequent–large have additional outliers between 800 and 2500 years.



mics fire scar records that are short due to any other process. Using this simple approach (Fall 1998), we explore only the sensitivity of estimates of WMPI to fire scar formation and degradation without attempting to model the many complex factors that determine such formation and degradation in the real world, such as fine-scale variation in fuel, the presence of a scar from a previous fire, tree species or age, subsequent fires, etc. (Swetnam and Baisan 2003).

Results

Analysis 1: Effect of the number of fire intervals

Estimates of median point fire intervals were subject to wide margins of error when calculated from small numbers of intervals ranging from 1.4 years for the AJT data set (6% of the median) to 20.1 years for the BGH data set (91% of the median) (Fig. 2).

Analysis 2: Simulated fire histories

As expected, true WMPI (computed for each 1 ha cell and then pooled across the landscape) differed among the four fire histories generated by our simulation model (Fig. 4). The interval distributions for all four are positively skewed, as expected given that they are drawn from a Weibull distribution. The overall point WMPI was 46 years for the frequent–large fire history, and estimates of the overall point WMPI for this fire regime type were considered accurate if they were within 4.6 years of this value (10%). The overall point WMPI was 78 years for the frequent–small (accurate if within 7.8 years), 83 years for the infrequent–large (accurate if within 8.3 years),

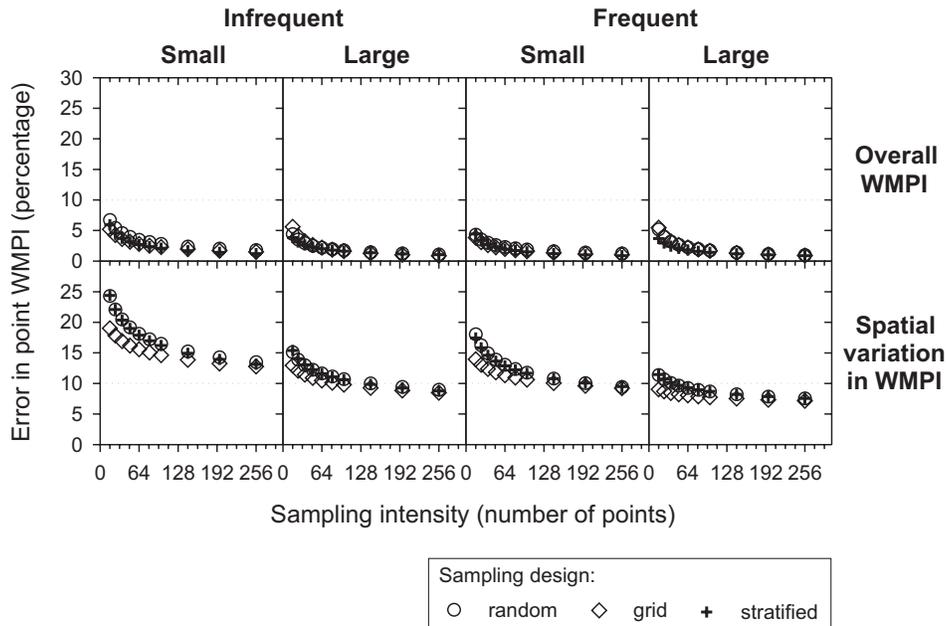
and 148 for the infrequent–small (accurate if within 14.8 years). Weibull median fire size was 306 ha for the frequent–large fire history, 167 ha for the frequent–small, 307 ha for the infrequent–large, and 171 ha for the infrequent–small. Within each fire regime type, WMPI computed at individual cells varied across the landscape by roughly an order of magnitude (Figs. 3b and 3c), indicating that different cells within the same landscape that are subject to the same underlying fire regime had very different expressions of that fire regime. The fire histories with infrequent fires were less smooth (i.e., cells near one another were less similar) than the fire histories with frequent fires (Moran's $I = 0.75$ – 0.79 versus 0.80 – 0.86 , respectively).

Analysis 3: Effect of sampling design and intensity

Estimates of overall WMPI (computed at cells and pooled over the landscape) were accurate (<10% error) for all three sampling designs and all sampling intensities (16–256 points sampled; top plots in Fig. 5). The accuracy of estimated overall WMPI increased (i.e., percent error decreased) as sampling intensity increased (i.e., number of sampling points increased), but there was little difference in accuracy among sampling designs, regardless of fire regime type or sampling intensity. The maximum error in overall WMPI from this analysis was 7%.

In contrast, the accuracy of estimated spatial variation in WMPI varied with all three factors (bottom plots in Fig. 5) but more strongly with fire regime type than with sampling design or intensity. For the infrequent–small fire regime, estimates were not accurate for any sampling design, regardless of the number of sampling points. Accurate estimation

Fig. 5. Error in replicated estimates of WMPI resulting from different sampling designs, sampling intensities, and fire regime types (analysis 3) (Fig. 1; Table 1). True overall WMPI is 148 years for the infrequent–small fire history, 83 for the infrequent–large, 78 for the frequent–small, and 46 for the frequent–large. A broken line indicating 10% error is shown for reference.



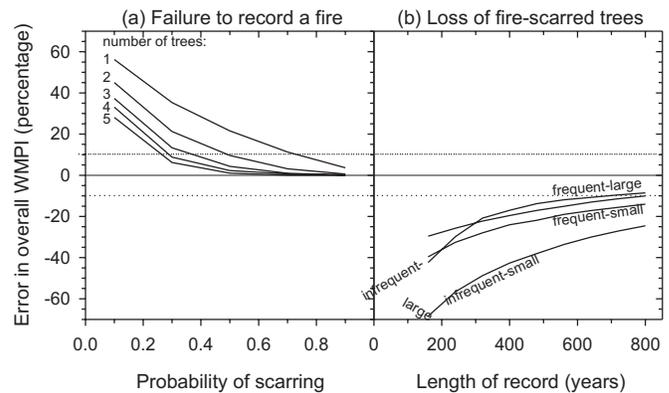
of spatial variation in WMPI for the frequent–small fire regime required 196–256 sampling points, for the infrequent–large 100–144 sampling points, and for the frequent–large 16–49 sampling points. Similar to the overall estimates of WMPI, accuracy in estimates of spatial variation in WMPI increased with increasing number of sampling points for all fire regime types, but the gridded sampling design yielded slightly more accurate results regardless of fire regime type or sampling intensity. The maximum error in spatial variation in this analysis was 24%.

Analysis 4: Effect of degradation of the fire scar record

The accuracy of estimates in overall WMPI was affected by both failure to record a fire and the loss of fire-scarred trees over time. While these effects were similar in magnitude, they were opposite in sign, with failure to record a fire tending to overestimate WMPI and shortened length of record tending to underestimate WMPI. For failure to record a fire, accuracy in WMPI was affected by both the number of trees sampled and the probability of scarring (Fig. 6), with accuracy increasing as number of trees or probability of scarring increased. For example, in the infrequent–small fire regime type, estimates of WMPI were accurate (<10%) for a single tree if the probability of scarring was greater than 0.9. However, accurate estimates could still be obtained for a much lower probability of scarring (0.3) if a greater number of trees were sampled (five trees). The maximum error in overall WMPI from this analysis was 56%. Results for the other three fire regime types were of the same magnitude (not shown).

For the loss of fire-scarred trees over time, accuracy in estimates of overall WMPI were affected by both fire regime type and record length. Overall WMPI was accurate (<10% error) only for very long records (>720 years) for the frequent–large fire regime type. Accuracy in overall WMPI increased

Fig. 6. Error in replicated estimates of overall WMPI (computed at 1 ha cells and pooled over the landscape) resulting from degradation of the fire scar record (analysis 4) (Fig. 1; Table 1). The errors presented in Fig. 6a are for the infrequent–small fire history, but the errors for the other three fire regime types were of similar magnitude. The length of record is the minimum length at which 80% of the cells have no fire intervals. A broken line indicating 10% error is shown for reference.



with increasing record length. The maximum error in overall WMPI from this analysis was 68%.

Discussion

The accuracy of the WMPI that we estimated from our simulated fire histories was affected by all of the factors we investigated: sampling design and intensity and degradation of the fire scar record. The greatest potential source of error that we found was degradation of the fire scar record, i.e., the probability of scarring and the loss of fire-scarred trees. Although the maximum error in the estimate of overall WMPI was of comparable magnitude for both forms of deg-

radation, they introduced biases of opposite sign. When the probability of scarring was low and (or) the number of trees from which fire records were composited at a point was low, the WMPI was overestimated because removing individual fire scars resulted in intervals that were longer than those that actually occurred. In contrast, when fire-scarred trees were lost over time, the WMPI was underestimated because longer fire intervals were preferentially lost as the length of the record was shortened (i.e., did not extend as far back in time for our simulations). Thus, WMPIs computed from fire histories with short records and long fire intervals are likely to be inherently less certain than those with long records and short intervals. However, the magnitude of the impact of degradation that we observed here is likely higher than for real fire histories because it depends on the total length of the record. Our record length was unrealistically long for fire scar records (4000 years), although not beyond the range of fire records from charcoal (e.g., Greenwald and Brubaker 2001; Hallett et al. 2003) and so included some unrealistically long extreme fire intervals (e.g., 2500 years). Both types of degradation introduced error into the estimate of the WMPI by reducing the number of intervals from which the WMPI could be estimated, similar to the results of our analysis 1 (Fig. 2) in which the accuracy of the WMPI increased as the number of intervals increased. These results apply to intervals reconstructed at a single point on the landscape or to intervals in a composite record made from trees sampled within an area of any size. We used the Weibull distribution but suggest that we would have obtained similar results if we had drawn our simulated fire histories from another of the distributions that are commonly used to characterize fire intervals (McCarthy et al. 2001). In the real world, some points on a landscape may lack sufficient intervals to characterize a WMPI for that point, e.g., forests that typically sustain infrequent, high-severity fires. Associating a measure of confidence in the WMPI for each sampled point, such as the number of intervals used to compute that WMPI, would help identify where fire history data should be interpreted with caution.

The interaction of fire size and fire frequency was a primary driver of spatial complexity in our model. Spatial variation in point fire intervals was lowest for the frequent-large regime and highest for the infrequent-small regime. Furthermore, the regimes with small fires resulted in patterns of point fire intervals that retained the influence of forest type, whereas the regimes with large fires yielded relatively homogenous patterns. Although most real landscapes include more complex topography and patterns of vegetation than our relatively simple landscape, we suggest that the sources of error in estimates of WMPI that we simulated are likely to be important across a broader range of fire regime types and landscape complexity than we simulated. For example, many surface fire regimes reconstructed from tree rings have WMPI that are shorter or longer than those that we simulated here. We expect that regimes with shorter intervals would be less susceptible to errors arising from short record lengths, whereas those with longer intervals would be more so. More complex landscapes that include topography, barriers to fire spread, and (or) more diverse vegetation would likely contribute to high spatial heterogeneity in point fire intervals (Suffling

1993; Camp et al. 1997; Stephens 2001) and thus would require many sampling points to accurately estimate spatial variation in WMPI. Fire regimes with very large or very many fires would likely yield relatively homogeneous spatial variation in point fire intervals, similar to some sites in Arizona for which relatively small differences in accuracy were observed among sampling methods and intensities (Van Horne and Fulé 2006). Finally, although we did not consider interactions among potential sources of error, in the real world, they act simultaneously.

In our simulations, the gridded sampling design was most efficient at capturing spatial variation in WMPI, as has been shown to be generally true when predicting spatial pattern from point data (Burgess and Webster 1980; Haining 2003). We assessed accuracy from maps in which mean fire intervals were interpolated between sampled points, which is not often done for fire history studies. Interpolation is fundamentally dependent on the distance between points and is less reliable when those spaces are large than when they are small (Press et al. 1992), which may be another reason gridded sampling was more efficient in our simulations.

The accuracy of estimates of fire frequency from fire scars has been the subject of recent debate (Baker and Ehle 2001; Fulé et al. 2003; Baker 2006; Fulé et al. 2006; Kou and Baker 2006; Van Horne and Fulé 2006). The magnitude of error that we found was in some cases similar but in general not as great as that found in another simulation study (Kou and Baker 2006). Our interest was in assessing errors in point fire frequency, so we only composited intervals across 1 ha cells. As a consequence, the errors that we observed in point fire intervals were not compounded by spatial heterogeneity in fire intervals and the well-known scale dependence of composite fire intervals that decrease as the compositing area increases (Dieterich 1980; Arno and Petersen 1983).

Fire histories are reconstructed for a broad range of purposes, some of which do not include accurate estimation of overall mean fire intervals or their spatial variation. For example, studies of the climate drivers of fire through time do not require systematic sampling (e.g., Swetnam and Betancourt 1990; Swetnam and Baisan 2003). Furthermore, while we could accurately estimate overall WMPI for our simulations with a small number of points (only 16 points over our 2500 ha landscape), such low numbers of sampled points may not yield accurate reconstructions of fire size. We did not simulate the full range of possible spatially explicit sampling designs. For example, targeted sampling in which fire-scarred trees are judgmentally located across landscapes to maximize record length has yielded accurate reconstructions of mean fire intervals in Arizona (e.g., Van Horne and Fulé 2006). We compared our analyses using an arbitrary accuracy cutoff of 10%, but this cutoff may not be appropriate for all fire regimes. For example, at sites with frequent fires, e.g., 6–10 years (Grissino-Mayer 1999), an error of 10% in the WMPI would be 0.6–1 year, which may not be ecologically meaningful.

Our findings emphasize the need to consider variability within and among fire regimes, as well as errors that may be present in the record available for sampling, in the design of fire history sampling projects. In many cases, particularly where temporal depth is limited and fire intervals are long, this variability results in significant uncertainty in fire inter-

val estimates. Management goals based on fire history data should reflect this uncertainty and bracket desired outcomes appropriately.

Acknowledgements

We thank Penelope Morgan, Brendan Ward, Marc Weber, and two anonymous reviewers for helpful review comments.

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