Stochastic Representation of Fire Behavior in a Wildland Fire Protection Planning Model for California

J. Keith Gilless and Jeremy S. Fried

ABSTRACT. A fire behavior module was developed for the California Fire Economics Simulator version 2 (CFES2), a stochastic simulation model of initial attack on wildland fire used by the California Department of Forestry and Fire Protection. Fire rate of spread (ROS) and fire dispatch level (FDL) for simulated fires "occurring" on the same day are determined by making coordinated draws from compound distributions characterizing 2 PM fire behavior indices such as ROS, then adjusting these draws using diurnal adjustment coefficients derived from hourly fire weather observations. Statistical examination of historical fire occurrence and predicted behavior data validated CFES2's use of independent fire occurrence and fire behavior modeling processes. For. Sci. 45(4):492–499.
Additional Key Words: CFES2, initial attack, fire rate of spread, burning index, fire.

Simulation models of initial attack on wildland fire are important tools for wildland fire protection planning, and several new models have been recently developed or enhanced, including CFES2 (Fried and Gilless 1988a, 1999), LEOPARDS (Hirsch 1997), Kitral (Julio et al. 1997), ARCAR41-CARDIN (Rodriguez y Silva 1997), FFMDSS (Shur 1995), and the National Fire Management Analysis System (NFMAS) (USDA Forest Service 1985). Sensitivity analysis of NFMAS indicates that such models are particularly sensitive to the methods and parameters used to characterize fire behavior (Dimitrakopoulos 1985).

The fire behavior component of a simulation model of initial attack planning on wildland fire usually determines, for each simulated fire: (1) fire rate of spread (ROS); and (2) fire dispatch level (FDL) [or fire intensity level]. ROS is particularly important in models that explicitly track the perimeter growth of simulated fires during initial attack. FDL, which is usually determined by reference to a fire behavior characteristic (e.g., ROS or flame length) or danger rating index (e.g., Burning Index (BI) or Energy Release Component (ERC) (Pyne et al. 1996)), plays a role in the determination of which firefighting resources are dispatched to a fire, and which firefighting tactics they will employ (e.g., head or tail attack). (Note: The FDL concept represents a simplification of the NFMAS approach to determining dispatch based on Fire Intensity Level.)

Simulation models of initial attack planning usually address ROS by either: (1) simulating each fire that occurred in some "historical season"; or (2) simulating a limited number of "representative fires" at specific percentile values (e.g., 50^{th} and 90^{th}) from the ROS distribution defined by reference to the fires that occurred in one or more prior fire seasons. Either approach requires that a database of historical fires be queried to identify the date, time, and appropriate fuel model for the fires that occurred in a given protection area. These data are typically then matched with fire behavior characteristics and indices (ROS, BI, etc.) for the corresponding dates and fuel models predicted using archived 2 PM fire weather data (Furman and Brink 1975, Helfman et al. 1980, Yancik and Roussopoulos 1982), possibly adjusting the values for the time of day at which fires occurred. A FDL is then determined for each fire by comparing one of these characteristics and indices with previously established thresholds. Selected percentile values (e.g., 50th and 90th) for ROS can then be determined, by FDL, for representative fire simulations.

Both the historical season and representative fire approaches have serious limitations for representing the stochastic processes underlying fire occurrence and behavior.

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Simulating sequences of historical fires may mask or overstate localized problems in the fire protection system. Limited historical records are likely to understate or overstate the relative frequency of days on which very high numbers of fires occur, and to increase the error associated with estimates of statistics such as the 90th percentile values. Both methods, by using fires rather than days as the basis for an observation, employ a sampling frame that may be problematic in areas where the fire load is largely the result of human activity rather than natural causes. A particularly subtle problem with using fire weather data only from days on which fires actually occurred rather than for all days for which fire weather was recorded is that gaps in fire weather data most frequently occur at the onset of a period of significant fire activity (Bunton 1997). The automated stations commonly deployed today will eventually remedy this situation; however, the data sets that have been generated by such stations are as yet too short to serve as the basis for the modeling approach described in this paper.

A particularly severe limitation of the representative fire method is the assumption that the results generated by simulations of initial attack on fires at an "average" ROS (i.e., 50th percentile value) can be extrapolated to characterize the results of initial attack over a wide range of ROS values.

California Fire Economics Simulator Version 2

The California Fire Economics Simulator version 2 (CFES2) is a clock-driven, event-based, quasi-spatial stochastic simulator of initial attack on wildland fires. CFES2 was developed to assist wildland fire protection planning by the California Department of Forestry and Fire Protection (CDF) (Fried and Gilless 1999). CFES2 can be used to play a variety of "what-if" games involving hypothetical changes to fuels, climate, firefighting strategies, and tactics, dispatch criteria, fireline productivity, detection time, availability of firefighting resources, fire prevention, deployment rules, accessibility, and staffing schedules.

The design and validation of CFES2's stochastic modules for: (1) fire containment (Fried and Fried 1996); (2) fireline production rates (Fried and Gilless 1989); and (3) fire occurrence (Fried and Gilless 1988b) have been previously reported in the literature. This paper describes the design and validation of CFES2's fire behavior module.

The design objectives for CFES2's fire behavior module were to: (1) fully utilize historical fire occurrence and behavior data; (2) allow for projected fire behavior characteristics and indices other than ROS to be used to determine FDL; (3) base fire simulations on the full potential distribution of ROS; and (4) ensure consistent fire behavior for all fires that "occur" on the same day.

These design objectives highlight the importance of the linkages between the representation of fire behavior and fire occurrence in a stochastic simulation model of initial attack. CFES2's occurrence module was designed to generate stochastic sequences of fire ignitions in time and space that would mimic historically observed patterns, primarily because of the CDF's need for a model that was capable of realistic simulation of the consequences of multiple fires occurring on the same day within a ranger unit. Evaluation of the degree to which the design objectives for CFES2's fire behavior module were met therefore necessarily involves evaluation of its interactions with the fire occurrence module.

Data

Parameterization of CFES2's fire behavior module draws on three data sources: (1) fire history databases for CDF ranger units; (2) 2 PM fire weather observations from AFFIRMS weather stations (Furman and Brink 1975, Helfman et al. 1980, Yancik and Roussopoulos 1982); and (3) hourly fire weather observations from Remote Automated Weather Stations (RAWS) (Warren and Vance 1981) (Table 1). Data from the Santa Clara, Riverside, and Nevada-Yuba-Placer ranger units were analyzed for this article (Figure 1). These ranger units span a wide range of vegetation types, topographic conditions, climatic conditions, and values at risk. Fire management analysis zones (FMAZs—defined by relatively homogeneous fuels and values at risk) and AFFIRMS and RAWS locations are shown for one of the ranger units (Santa Clara) in Figure 2.

Daily observations from AFFIRMS weather stations were processed with FBDMOD (CDF 1992), a PC version of FIRDAT (Main et al. 1990), for all National Fire Danger Rating System (NFDRS) fuel models (Deeming et al. 1977) designated by ranger unit staff as descriptive of their FMAZs. For each ranger unit, this process generated a database of fuel model-specific, 2 PM fire behavior indices.

Table 1. Attributes of historical fire and weather data used in the analysis reported here, by ranger unit.

Attribute	Santa Clara	Nevada-Yuba-Placer	Riverside
Period of fire history coverage	1986–1994	1986–1994	1984–1991
Mean number of fires per year	557	539	1290
Mean number of days per year with one or more fires	207	205	251
Protected area (ha)	554,483	360,418	404,808
Mean area burned per year (ha)	2,122	2,118	4,034
AFFIRMS station name	Morgan Hill	Wolf Creek Lookout	Anza
AFFIRMS station identifier	43903	41805	45616
AFFIRMS station location (lat/long)	37.10N 121.70W	39.10N 121.10W	33.56N 116.67W
AFFIRMS station elevation (m)	98	803	1,213
NFDRS fuel models used	A, B, F, G	A, B, F, G	A, B, T
RAWS station name	Livermore	Not applicable	Not applicable
Years of RAWS data	< 2	Not applicable	Not applicable

Figure 1. Nevada-Yuba-Placer (NEU), Santa Clara (SCU), and Riverside (RRU) ranger units.

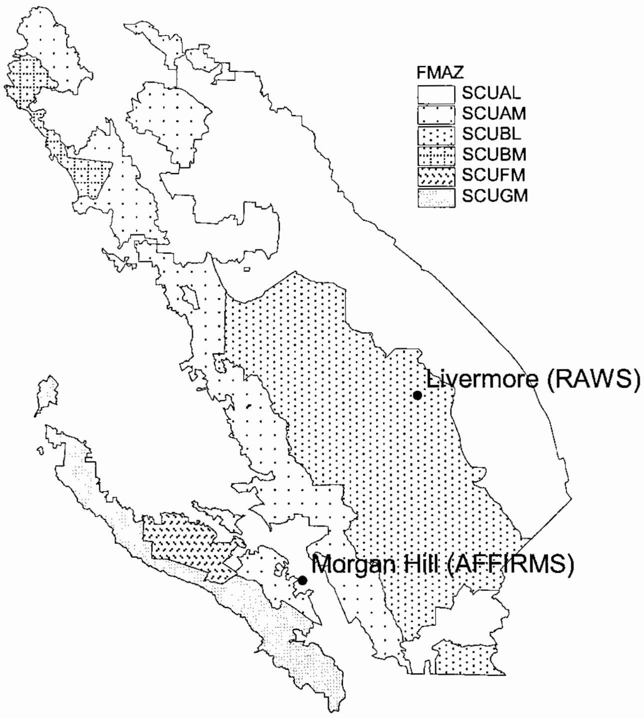

Figure 2. FMAZs, AFFIRMS, and RAWS weather stations for the Santa Clara ranger unit.

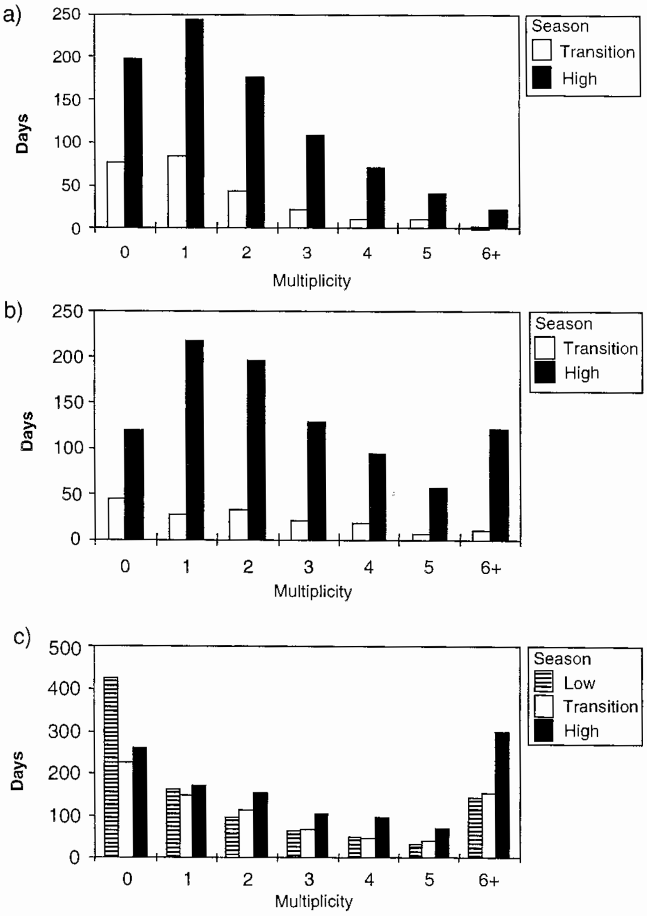

Figure 3. Multiplicity history (zero refers to days without fires), by season, for: (a) Santa Clara ranger unit (1980–1988); (b) Nevada–Yuba–Placer ranger unit (1986–1994); and (c) Riverside ranger unit (1984–1991).

The merged databases were queried to generate two variables characterizing fire occurrence: (1) Fireday (equal to 1 for days on which fires occurred, and equal to 0 otherwise); and (2) Multiplicity (defined only for days with Fireday = 1, and equal to the number of fires that occurred on the ranger unit on a given day). The frequency distributions for Multiplicity for all three ranger units are shown in Figure 3 for the "Low," "Transition," and "High" fire seasons (defined by fire load). As noted in Fried and Gilless (1988b), Multiplicity for days on which Fireday = 1 (i.e., for days on which a fire occurs) is well characterized by a geometric distribution.

Hourly observations from RAWS weather stations were processed with the HISTROS program (CDF 1991) for the same NFDRS fuel models for each ranger unit to produce databases of hourly fire behavior indices for use in characterizing diurnal variation in fire behavior.

2 PM ROS and BI Distributions

The distributions of 2 PM ROS and BI values were consistently bimodal, for all fuel models, for all ranger units; distributions for the Santa Clara ranger unit are shown in Figures 4a and 5a. These distributions have one peak corresponding to days with low ROS (or BI), and another corresponding to days with high ROS (or BI).

CFES2's fire behavior module therefore characterizes 2 PM ROS (or BI) using a compound distribution. Low values are described by two parameters: (1) the probability of 2 PM fire behavior being "drawn" from this portion of the distribution; and (2) a constant ROS (or BI) value to describe the behavior of such fires. High values are described by: (1) α and β parameters of a beta distribution; and (2) minimum and

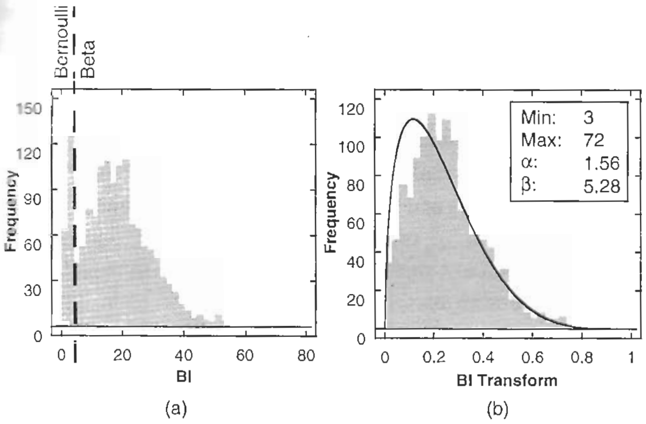

Figure 4. BI, calculated using data from AFFIRMS weather station 43903, fuel model A, slope class 2, high fire season: (a) frequency histogram, with dashed vertical line defining ranges modeled with Bernoulli (left) and beta (right) distributions; (b) beta range frequency histogram and fitted beta distribution, with BI values scaled to the interval between zero and one.

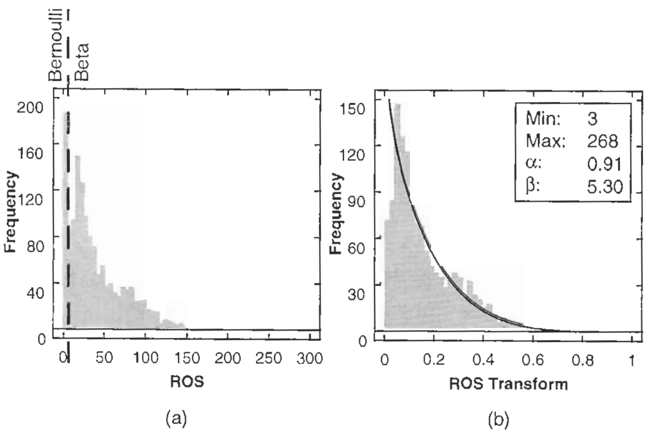

Figure 5. ROS calculated using data from the AFFIRMS weather station 43903, fuel model A, slope class 2, high fire season: (a) frequency histogram, with dashed vertical line defining ranges modeled with Bernoulli (left) and beta (right) distributions; (b) beta range frequency histogram and fitted beta distribution, with ROS values scaled to the interval between zero and one.

maximum ROS (or BI) values (Figures 4b and 5b). Distributions are estimated separately for low, transition, and high fire seasons defined for each ranger unit by interpretation of abrupt changes in fire load over the course of the year.

ROS and FDL Behavior Links

For each FMAZ in a ranger unit, CFES2 uses one *behavior link* to determine a fire's FDL and one to determine its ROS—a behavior link being defined by a weather station, a fuel model, a slope class, a climate class, and whether herbaceous vegetation is annual or perennial. The FDL and ROS behavior links might be the same for a given FMAZ if FDL is based on ROS. However, many CDF ranger units currently base FDL on *BI or some other index of fire behavior,* so CFES2 was designed to allow for flexibility in this regard. Whatever index is used for setting FDL, the thresholds between low and medium and between medium and high FDL must be specified for each FMAZ.

Coordinated Fire Behavior

CFES2's fire behavior module employs a coordinated fire behavior modeling process to ensure consistency in the behavior of fires that occur on the same day: (1) a single random draw is made for the day from a uniform random distribution between 0 and 1; (2) the percentile position thus determined is used to select 2 PM values from all of the ROS (or BI) distributions that must be sampled to determine ROS and FDL for the fires occurring on that day; and (3) these 2 PM values are adjusted for the time of day at which each fire occurs.

Diurnal Adjustment Coefficients

CFES2's fire occurrence module assigns start times to simulated fires based on random draws from beta or Poisson distributions for time of day. For the fire behavior module, diurnal adjustment coefficients for 2 PM ROS (or BI) values were derived by: (1) taking hourly fire behavior characteristic or index values estimated from RAWS data; (2) dividing each value by the value at 2 PM on the same day; and then (3) determining the median value of this ratio for each hour of the day. Diurnal adjustment coefficients for one ROS and one BI distribution for the Santa Clara ranger unit are shown in Table 2. Note that the 2 PM coefficient is always equal to one, by construction.

Validation

For all three ranger units, honest significant difference (HSD) plots (Tukey 1977) of 2 PM ROS (and BI) percentile

Table 2. Diurnal adjustment coefficients for 2 PM ROS and BI values calculated using Livermore RAWS data, fuel model A, slope class 2, high fire season.

AM hour	ROS	BI	PM hour	ROS	BI
12	0.06	0.08	12	0.78	0.81
1	0.05	0.06	1	0.94	0.95
2	0.05	0.06	2	1.00	1.00
3	0.04	0.06	3	0.95	0.95
4	0.05	0.06	4	0.84	0.83
5	0.04	0.06	5	0.67	0.62
6	0.04	0.05	6	0.43	0.40
7	0.04	0.05	7	0.22	0.22
8	0.06	0.07	8	0.13	0.14
9	0.17	0.21	9	0.08	0.10
10	0.34	0.37	10	0.06	0.08
11	0.58	0.60	11	0.06	0.07

values for days on which fires did occur (Fireday = 1) and did not occur (Fireday = 0), by fuel model, provided only weak support for complete independence between fire occurrence and fire behavior, with ROS clearly being drawn from a distribution of higher values for days on which fires occurred (Figure 6). However, the magnitude of the difference in mean percentile values was generally no more than ten points. Considering only days on which fires had occurred, 2 PM ROS (and BI) percentile values were unaffected by Multiplicity (Figure 7).

To evaluate CFES2's method of coordinating fire behavior by using a draw from a uniform random distribution between 0 and 100 to generate a percentile on which to base all draws from 2 PM ROS (or BI) distributions, Pearson correlation coefficients were calculated between the percentile ROS and BI values, across NFDRS fuel models. For all three ranger units, these correlations were generally very high and significant, lying between 0.7 and 1.0 (Tables 3, 4, and 5).

Summary and Conclusions

It was clear from the beginning of CFES2's development that independence of the fire occurrence and fire behavior modules would dramatically reduce the difficulty of parameterizing the model. The failure of others to validate the relationship between fire danger rating and fire load (Haines et al. 1983) encouraged us to pursue such a strategy, although independence was never actually made a design objective. The results presented in this paper generally confirm the legitimacy of an assumption that fire occurrence and fire behavior can be modeled independently, although they do suggest that the distributions for fire behavior indices be estimated using data only from days on which fires did occur.

However legitimate the assumption of independence between fire occurrence and fire behavior, assuming independence in fire behavior for fires that occur on the same day is clearly inappropriate. This could produce contemporaneous fires in the same FMAZ with implausibly large differences in ROS. Modeling fire behavior for fires occurring on the same day is further complicated by the use of a fire behavior index other than ROS to determine FDL. Predictions of these indices are often based on an NFDRS fuel different from the one used to predict fire behavior. CFES2 solves this problem by allowing flexibility in the specification of fire behavior links to determine ROS and FDL, and using a random draw from a uniform random distribution to coordinate the values drawn from different fire behavior distributions for a given day.

For the CDF ranger units considered in this study, AFFIRMS fire weather data was available for 2 or 3 decades, while RAWS fire weather data was available for less than 2 yr. Utilizing AFFIRMS data to estimate 2 PM ROS (or BI) distributions, and utilizing RAWS data to estimate diurnal adjustment coefficients for values drawn from these distributions, represents a practical and efficient approach to characterizing fire behavior for simulation models. As additional RAWS data is archived, it might be possible to use RAWS data to directly estimate time-of-day specific distributions for fire behavior indices.

Additional research is needed to modify the procedure for diurnal adjustment of fire behavior to account for special events (e.g., Santa Ana winds in Southern California) where unusual diurnal patterns in fire behavior are observed. CFES2 was actually designed in anticipation of such research, and is coded to allow for probabilistic utilization of two sets of diurnal adjustment coefficients corresponding to "normal" or "special" conditions.

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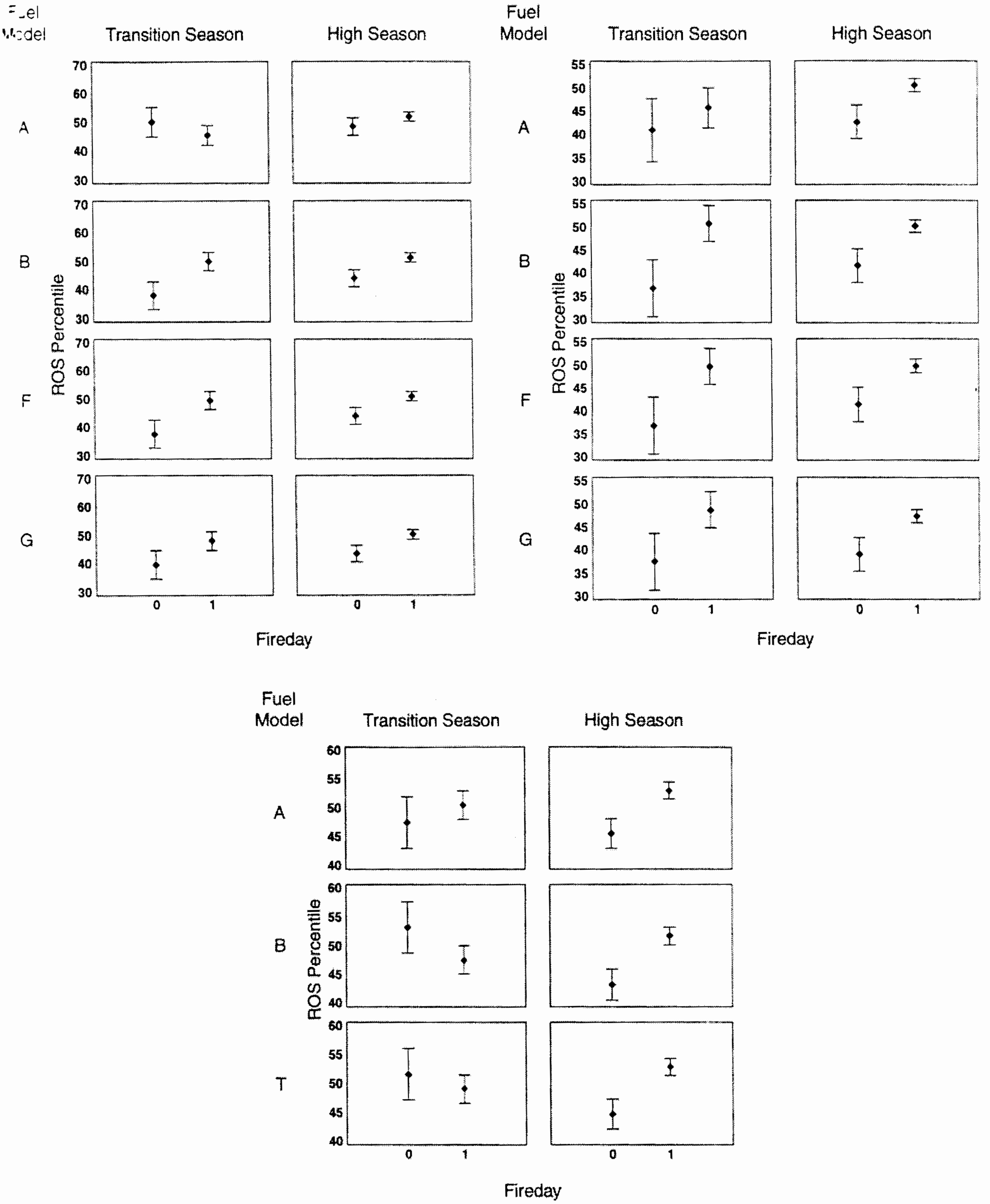

Figure 6. Means and 95.0 percent Tukey HSD intervals for ROS percentile values by Fireday, by NFDRS fuel model, for: (a) the Santa Clara ranger unit; (b) the Nevada–Yuba–Placer ranger unit; and (c) the Riverside ranger unit.

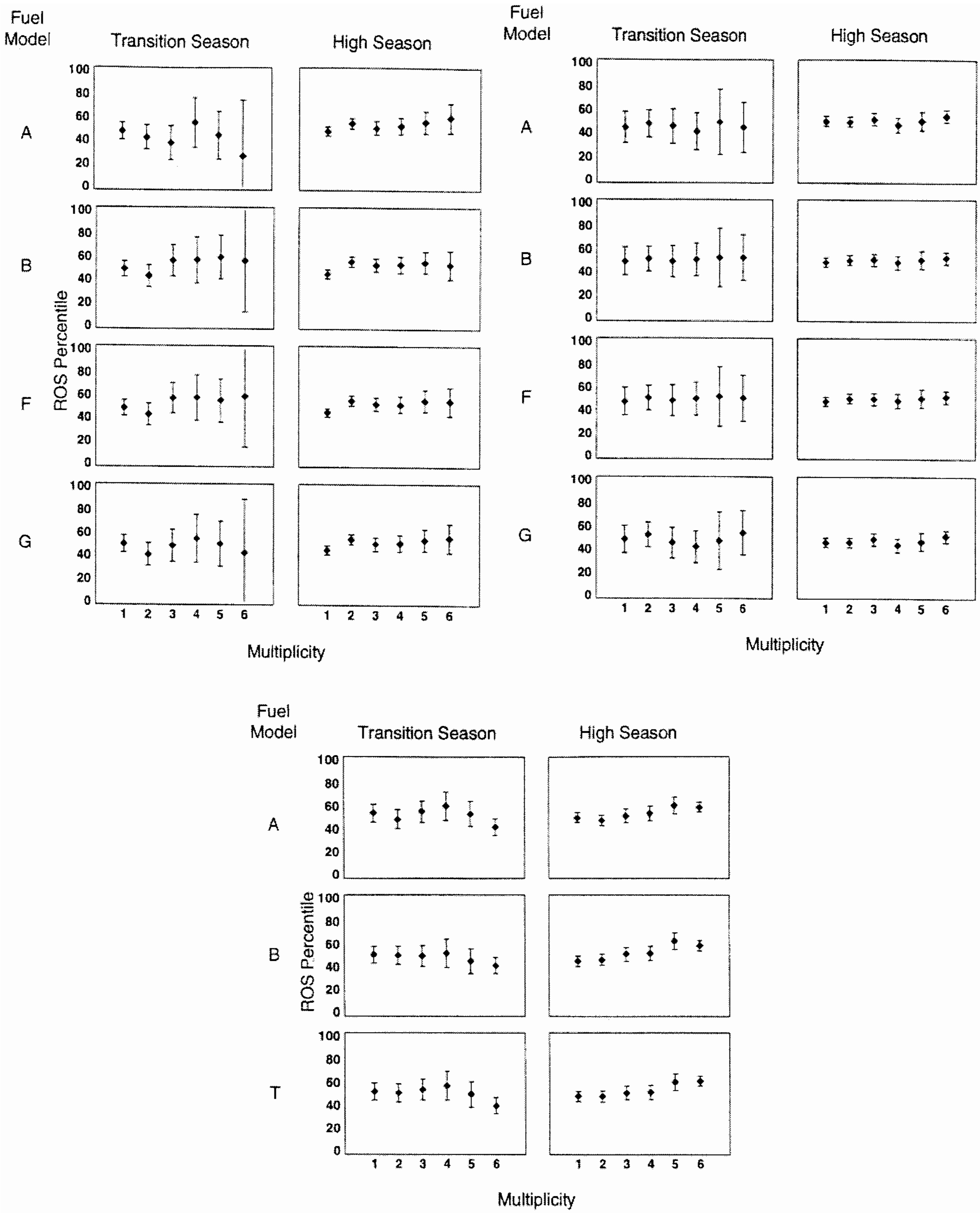

Figure 7. Means and 95.0 percent Tukey HSD intervals for ROS percentile values by Multiplicity, by NFDRS fuel model, for: (a) the Santa Clara ranger unit; (b) the Nevada–Yuba–Placer ranger unit; and (c) the Riverside ranger unit.

Table 3. Pearson correlations between 2 PM ROS and BI percentile values for four NFDRS fuel models, for the high fire season, for the Santa Clara ranger unit (n = 858).

	ROS Model B	ROS Model F	ROS Model G	BI Model A	BI Model B	BI Model F	BI Model G
ROS Model A	0.81	0.81	0.86	0.94	0.73	0.74	0.89
ROS Model B		0.98	0.97	0.70	0.89	0.90	0.93
ROS Model F			0.97	0.69	0.87	0.89	0.93
ROS Model G				0.77	0.88	0.89	0.96
BI Model A					0.73	0.74	0.86
BI Model B						0.99	0.91
BI Model F							0.93

Table 4. Pearson correlations between 2 PM ROS and BI percentile values for four NFDRS fuel models, for the high fire season, for the Nevada-Yuba-Placer ranger unit (n = 940).

	ROS Model B	ROS Model F	ROS Model G	BI Model A	BI Model B	BI Model F	BI Model G
ROS Model A	0.83	0.80	0.95	0.95	0.77	0.76	0.91
ROS Model B		0.96	0.84	0.86	0.95	0.92	0.95
ROS Model F			0.81	0.86	0.96	0.96	0.93
ROS Model G				0.88	0.77	0.76	0.94
BI Model A					0.87	0.87	0.91
BI Model B						0.98	0.90
BI Model F							0.89

Table 5. Pearson correlations between 2 PM ROS and BI percentile values for three NFDRS fuel models, for the high fire season, for the Riverside ranger unit (n = 943).

	ROS Model B	ROS Model T	BI Model A	BI Model B	BI Model T
ROS Model A	0.77	0.87	0.96	0.72	0.85
ROS Model B		0.83	0.79	0.88	0.86
ROS Model T			0.85	0.72	0.93
BI Model A				0.82	0.91
BI Model B					0.86

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