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# EVALUATING PRE- AND POST-FIRE PEAK DISCHARGE PREDICTIONS ACROSS WESTERN U.S. WATERSHEDS[1]

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ABSTRACT: This study reviews five models commonly used in post-fire hydrologic assessments: the Rowe Countryman and Storey (RCS), United States Geological Survey (USGS) Linear Regression Equations, USDA Windows Technical Release 55 (USDA TR-55), Wildcat5, and U.S. Army Corps of Engineers (USACE) Hydrologic Modeling System (HEC-HMS). The models are applied to eight diverse basins in the western United States (U.S.) (Arizona, California, Colorado, Montana, and Washington) affected by wildfires and assessed by input parameters, calibration methods, model constraints, and performance. No one model is versatile enough for application to all study sites. Results show inconsistency between model predictions for events across the sites and less confidence with larger return periods (25- and 50-year events) and post-fire predictions. The RCS method performs well, but application is limited to southern California. The USGS linear regression model has wider regional application, but performance is less reliable at the large recurrence intervals and post-fire predictions are reliant on a subjective modifier. Of the three curve number-based models, Wildcat5 performs best overall without calibration, whereas the calibrated TR-55 and HEC-HMS models show significant improvement in pre-fire predictions. Results from our study provide information and guidance to ultimately improve model selection for post-fire prediction and encourage uniform parameter acquisition and calibration across the western U.S.

(KEY TERMS: fire; runoff; modeling; prediction; watershed management; BAER assessment.)

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## INTRODUCTION

Wildfires alter land surfaces, land-atmosphere interactions, and hydrologic response (De Bano, 2000; Moody and Martin, 2001; Beringer *et al.*, 2003; Ice *et al.*, 2004; Prater and DeLucia, 2006; Pierson *et al.*, 2008; Cydzik and Hogue, 2009; Jung *et al.*, 2009; Montes-Helu *et al.*, 2009; Burke *et al.*, 2010). Wildfires are also occurring more frequently at the wildland-urban interface and impose threats on development and human populations (Radeloff *et al.*, 2005; Cannon and DeGraff, 2009). Climate change and increasing wildfire frequency add to post-fire hydrologic variability (Westerling *et al.*, 2006; Trouet *et al.*, 2008; Cannon and DeGraff, 2009), and the ability to accurately predict post-fire flood potential is vital for both human safety and effective and efficient management of state and regional resources.

The U.S. Department of Agriculture (USDA), U.S. Forest Service (USFS), and Burn Area Emergency Response (BAER) teams are deployed, as soon as

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conditions permit, to determine values at risk across the forests. BAER teams are also responsible for hydrologic predictions and focus on estimating potential increases in post-fire runoff and sediment that place downstream values at risk or threaten human life and natural resources. Hydrologic assessments undertaken by BAER teams vary by region, fire, modeler, accessibility, and ease of use (Foltz *et al.*, 2009), and generally there is a lack of consistency in post-fire hydrologic assessments. In addition, performance of many of the applied hydrologic models has not been well documented within the post-fire context.

Numerous models and techniques are available to predict post-fire peak discharge, varying significantly in complexity and ease of use. The operational BAER teams typically use empirical, event-based models to accommodate rapid assessment. A USFS survey on BAER models (Napper, 2010) found out that 26% of modelers use the U.S. Geological Survey (USGS) Linear Regression Model, 10% use the USDA Windows Technical Release 55 (TR-55), 23% use Curve Number (CN) methods (no specific model platform mentioned), 9% use Wildcat4 or Wildcat5, 20% use the Water Erosion Prediction Project (WEPP), 2% use the Fire Enhanced Runoff and Gully Initiation (FERGI), 8% use the Rowe Countryman and Storey (RCS), and 2% use the U.S. Army Corps of Engineers (USACE) and Hydrologic Modeling System (HEC-HMS) model. The BAER survey brings attention to the wide range of models being utilized by the wildfire community and the need for systematic approaches in their application (i.e., gathering parameters and adjusting models for post-fire conditions). In general, the BAER models have been extensively utilized and validated over various watersheds. However, they are rarely evaluated under post-fire conditions, where application of the models often falls outside the developed range of parameters resulting in unreliable predictions (Cydzik and Hogue, 2009; Chen *et al.*, 2013). Models chosen for review in the current study include the RCS, USGS Linear Regression Equations, TR-55, Wildcat5, and HEC-HMS. Although other empirical equations or methods have been developed that utilize peak discharge measurements from burned watersheds (Schaffner and Reed, 2005; Reed and Schaffner, 2007; Reed *et al.*, 2012; Moody, 2012), the current assessment focuses on a suite of models routinely used and recommended by our USFS collaborators.

The RCS method consists of LUTs for discharge and erosion rates for southern Californian watersheds based on *in situ* observations (Rowe *et al.*, 1949). Notable fires such as the 2003 Old and Grand Prix Fires, and the 2009 Station Fire in California, utilized the RCS method for BAER post-fire hydrological predictions and management assessments (Biddinger *et al.*, 2003; Moore *et al.*, 2009). The USGS Linear Regression Equations have been used to estimate peak discharge across the United States (U.S.), primarily under pre-fire conditions. The USGS method uses relations between discharge and climatic and physical characteristics of the contributing area and is often applied to ungaged sites where there is no observational data. The regression equations have been developed for each state and have been recently integrated into an interactive Geographic Information Systems (GIS) framework (U.S. Geological Survey, 2013). A modifier has also been developed to utilize the established equations for post-fire predictions (Foltz *et al.*, 2009).

The TR-55, Wildcat5, and HEC-HMS models utilize CN methodology, but vary by model parameters, constraints, and developed interface. Several of the models have been previously applied to notable fires such as the 2002 Hayman Fire (Wildcat4) (Robichaud *et al.*, 2003) and 2000 Valley-Complex (Soil Conservation Service (SCS) CN method) (Burned Area Emergency Rehabilitation Team, Valley Fire Complex, 2000), and the 2003 Old Fire (HEC-HMS) (Cydzik and Hogue, 2009). The CN method is noted for having more uncertainty in predictions when estimating at the extremes, especially during low-flow and low rainfall conditions (Hawkins, 1975). Cydzik and Hogue (2009) analyzed the HEC-HMS under both pre- and post-fire conditions. Results showed significant changes from pre- to post-fire parameter values as well as trends in several variables (initial abstractions, CN, and lag time) over a three-year recovery period. The CN returned to pre-fire values by the end of the second post-fire year, initial abstractions reached pre-fire conditions after the third rainy season, and the lag time remained lower than pre-fire values throughout the three-year study period (Cydzik and Hogue, 2009; Chen *et al.*, 2013).

The current study undertakes one of the first model intercomparison studies for a range of event-based hydrologic models utilized under both pre- and post-fire watershed conditions. We outline the various modeling platforms, parameter acquisition (inputs and outputs), and necessary parameter alterations for pre- and post-fire simulations. Specifically, the objectives of our work are to: (1) review a range of event-based hydrologic models utilized in post-fire modeling of peak flow events; (2) evaluate the models' performance across a range of diverse fire sites, including Arizona, southern and northern California, Colorado, Montana, and Washington; (3) demonstrate potential improvements in calibrated models where data are available; and (4) provide guidance on model constraints and application in diverse post-fire regimes. Ultimately, we hope to facilitate a uniform framework and calibration approach for improved post-fire hydrologic practices and modeling assessments across multijurisdictional fires in the western U.S.

## STUDY MODELS

Generally, the tested models include geomorphic parameters that describe the physical watershed including size, slope, or lengths (Table 1). Forcing data typically includes precipitation, storm intensity, or storm duration. In the current study, smaller basins (<13 km$^2$) are modeled as lumped (basin inputs and parameter are uniform) and larger watersheds are distributed (basin inputs and parameters vary by subbasin). In both cases, modeled basin outputs include either peak discharge (Qpk) or a complete discharge hydrograph at the outlet. After pre-fire models are established, models are altered using published literature or documentation to create post-fire models. It is important to note that the tested hydrologic models do not include algorithms for sediment or debris bulking factors. Bulking factors increase the clear water discharge to represent the high concentrations of sediment typical of post-fire conditions (Gusman *et al.*, 2011).

### *Rowe Countryman and Storey*

The RCS is a method for estimating flood peaks and erosion for basins within the national forests of southern California (Rowe *et al.*, 1949). The RCS establishes reasonable estimates through detailed LUTs of the average frequency and size of peak flow events and erosion rates associated with normal (unburned) conditions, the effect of burned vegetation, and the recovery of vegetation and hydrology with respect to time. Rowe *et al.* (1949) undertook extensive observations across southern California watersheds (along the coast from the Mexican border to San Luis Obispo) and developed relations for peak discharge frequencies for over 250 watersheds within five zones. Relations were then established between storm precipitation and post-fire peak discharge for watersheds in each specific storm zone and determined the changes in these flows for subsequent post-fire years. The method is still widely used for runoff estimates in southern Californian watersheds.

### *USGS Linear Regression Equations*

The USGS Linear Regression Equations are developed for estimating 2-, 5-, 10-, 25-, 50-, and occasionally 100-year peak discharge for ungaged sites across the U.S., generally for pre-fire conditions. The least squares regression equations are produced for broad regions using long-term discharge observations. In the current study, we implement regression equations previously developed for Region 14 (Arizona), Sierra (California), South Coast (California), Mountain (Colorado), Upper Yellowstone Central Mountain (Montana), and Region 4 (Washington). The general regional equations and variables used in this study are outlined below (coefficients provided in Table 2; formulas developed for English units):

Region 14, Arizona (Thomas *et al.*, 1997): $Q_t = kA^a(E/1000)^b$
Sierra, California (Waananen and Crippen, 1977): $Q_t = kA^aP^bH^c$
South Coast, California (Waananen and Crippen, 1977): $Q_t = kA^aP^b$
Mountain, Colorado (Vaill, 2000): $Q_t = kA^a(S + 1)^b$
Upper Yellowstone Central Mountain, Montana (Omang, 1992): $Q_t = kA^a(E/1000)^b(HE{+}10)^c$
Region 4, Washington (Sumioka *et al.*, 1998): $Q_t$ is the $kA^aP^b$

where $t$ is the recurrence interval years, $A$ is the watershed area [mi$^2$], $P$ is the mean annual precipitation [in], $H$ is the altitude index (average of

TABLE 1. Summary of Models Utilized in the Current Study, Including Model Developer, Platform for Application, Constraints on Watershed Size, and Model Outputs.

| Model | Creator | Platform | Most Suitable Watershed Size | Outputs |
|---|---|---|---|---|
| RCS | Rowe Countryman Storey | Look-up tables (LUTs) | N/A | Qpk, sediment |
| USGS Linear Regression | USGS | Regional USGS regression equations | >13 km$^2$ | Qpk |
| Curve Number (CN) Methods | | | | |
| TR-55 | USDA NRCS | WinTR-55 | <65 km$^2$ | Qpk and time, hydrograph |
| Wildcat 5 | USFS, Stream Team, Fort Collins, Colorado | Microsoft Excel macros (2003 or later) | <13 km$^2$ | Qpk and time, hydrograph |
| USACE HEC-HMS | U.S. Army Corps | Windows | Flexible | Storm hydrograph, Qpk and time |

TABLE 2. USGS Linear Regression Models and Coefficients for Pre-Fire Conditions (developed for English units) for Each Recurrence Interval Used in the Current Study, Where $t$ Is the Recurrence Interval [years], $A$ Is the Watershed Area [mi$^2$], $P$ Is the Mean Annual Precipitation [in], $H$ Is the Altitude Index (average of elevations at points 10 and 85% along the channel in thousands of feet), $E$ Is the Mean Basin Elevation [ft], $S$ Is the Slope, and HE Is the High Elevation Index (percentage of the total basin area above 6,000 ft).

| State | Region | Sites | Equation | $t$ = 2 | $t$ = 5 | $t$ = 10 | $t$ = 25 | $t$ = 50 |
|---|---|---|---|---|---|---|---|---|
| Arizona | Region 14 | Frye | $Q_t = kA^a(E/1000)^b$ | $k$ = 0.124, $a$ = 0.845, $b$ = 1.44 | $k$ = 0.629, $a$ = 0.807, $b$ = 1.12 | $k$ = 1.43, $a$ = 0.786, $b$ = 0.958 | $k$ = 3.08, $a$ = 0.768, $b$ = 0.811 | $k$ = 4.75, $a$ = 0.758, $b$ = 0.732 |
| California | Sierra | Bull #3, Rock | $Q_t = kA^aP^bH^c$ | $k$ = 0.24, $a$ = 0.88, $b$ = 1.58, $c$ = −0.80 | $k$ = 1.20, $a$ = 0.82, $b$ = 1.37, $c$ = −0.64 | $k$ = 2.63, $a$ = 0.80, $b$ = 1.25, $c$ = −0.58 | $k$ = 6.55, $a$ = 0.79, $b$ = 1.12, $c$ = −0.52 | $k$ = 10.4, $a$ = 0.78, $b$ = 1.06, $c$ = −0.48 |
| California | South coast | Arroyo, Devil | $Q_t = kA^aP_b$ | $k$ = 0.14, $a$ = 0.72, $b$ = 1.62 | $k$ = 0.40, $a$ = 0.77, $b$ = 1.69 | $k$ = 0.63, $a$ = 0.79, $b$ = 1.75 | $k$ = 1.10, $a$ = 0.81, $b$ = 1.81 | $k$ = 1.50, $a$ = 0.82, $b$ = 1.85 |
| Colorado | Mountain | Hayman | $Q_t = kA^a(S + 1)^b$ | $k$ = 11.0, $a$ = 0.663, $b$ = 3.465 | $k$ = 17.9, $a$ = 0.677, $b$ = 2.739 | $k$ = 23.0, $a$ = 0.685, $b$ = 2.364 | $k$ = 29.4, $a$ = 0.695, $b$ = 2.004 | $k$ = 34.5, $a$ = 0.700, $b$ = 1.768 |
| Montana | Upper Yellowstone Central mountain | Fridley | $Q_t = kA^a(E/1000)^b \times (HE + 10)^c$ | $k$ = 0.177, $a$ = 0.85, $b$ = 3.57, $c$ = −0.57 | $k$ = 0.960, $a$ = 0.79, $b$ = 3.44, $c$ = −0.82 | $k$ = 2.71, $a$ = 0.77, $b$ = 3.36, $c$ = −0.94 | $k$ = 8.54, $a$ = 0.74, $b$ = 3.16, $c$ = −1.03 | $k$ = 19.0, $a$ = 0.72, $b$ = 2.95, $c$ = −1.05 |
| Washington | Region 4 | Andrews | $Q_t = kA^aPb$ | $k$ = 0.025, $a$ = 0.880, $b$ = 1.70 | N/A | $k$ = 0.179, $a$ = 0.856, $b$ = 1.37 | $k$ = 0.341, $a$ = 0.850, $b$ = 1.26 | $k$ = 0.505, $a$ = 0.845, $b$ = 1.20 |

elevations at points 10 and 85% along the channel in thousands of feet), $E$ is the mean basin elevation [ft], $S$ is the slope, and HE is the basin high elevation index (percentage of the total basin area above 6,000 ft).

*Curve Number Models*

The CN approach was developed by the USDA Natural Resources Conservation Service (NRCS) to estimate runoff volume primarily from agricultural settings (U.S. Department of Agriculture, Soil Conservation Service, 1991). The SCS CN method considers rainfall, NRCS hydrologic soil groups, land cover type, treatment and conservation practices, hydrologic conditions, and topography. The selected CN value is a function of land cover type, soil properties, and antecedent moisture conditions, which can be estimated from LUTs or geospatial datasets. The SCS method considers four hydrologic soil groups (A, B, C, and D), categorized by similar structure, texture, infiltration, and runoff characteristics (i.e., degree of swelling when saturated, transmission rate of water) (U.S. Department of Agriculture, Natural Resources Conservation Service, 2007). Soil group runoff potential increases from low (A) to high (D) and decreases from free water transmission (A) to restricted water transmission (D). The TR-55 models accommodate three predefined rainfall distributions types — Types I, IA, and III, which are based on climate zones across the U.S. (U.S. Department of Agriculture, Natural Resources Conservation Service, 2009). Types I and IA represent the Pacific maritime climate (wet winters and dry summers). Type IA is the most gradual rainfall distribution type and Types II and III represent similar distributions of intense, short duration rainfall.

The depth of runoff ($P_e$) is estimated using the CN and cumulative precipitation for a specified duration and the empirical formulation of the uniform loss applied throughout a storm includes (Mays, 2001):

$$S = \frac{1000}{\mathrm{CN}} - 10, \tag{1}$$

where $S$ is the storage (potential maximum retention) and CN is the estimated CN value.

$$I_a = (0.1)S, \tag{2}$$

where $I_a$ is the initial abstractions [in] (Baltas *et al.*, 2007).

$$P_e = \frac{(P - I_a)^2}{P - I_a + S}, \tag{3}$$

where $P_e$ is the precipitation excess (runoff depth) [in] and $P$ is the total storm precipitation [in]. For consistency, the SCS Dimensionless Unit Hydrograph (UH), an empirical method used to route flow to a designated output location or design point, is selected for use in the Wildcat5, TR-55, and the HEC-HMS models. The SCS UH method uses time of concentration, $T_c$, which is defined as the time for a particle of water to travel from the furthest point of the watershed to the design point

(U.S. Department of Agriculture, Soil Conservation Service, 1991; Mays, 2001):

$$T_c = \frac{L^{0.8}(S+1)^{0.7}}{1140(Y^{0.5})}, \tag{4}$$

where $T_c$ is the time of concentration [hours], $L$ is the watershed length [ft], and $Y$ is the average watershed slope [%]. Lag time is subsequently defined as:

$$T_L = 0.6T_c, \tag{5}$$

where $T_L$ is the lag time [hours], which is the time from the center of mass of a rainfall event to the time of peak discharge. The time to peak ($T_p$) is defined as:

$$T_p = 0.67T_c, \tag{6}$$

where $T_p$ is the time to peak [hours]; which is the time from the beginning of rainfall to the time of peak discharge. Base time ($T_b$) is defined as:

$$T_b = 2.67T_p, \tag{7}$$

where $T_b$ is the base time [hours], which is the duration of the storm response. Finally, peak discharge ($Q_p$) is defined as:

$$Q_p = 484\frac{A}{T_p}, \tag{8}$$

where $Q_p$ is the peak discharge [cfs] and $A$ is the watershed area [mi$^2$].

### *Wildcat5*

The Wildcat5 is used extensively in U.S. Forest Service applications to wildlands (Hawkins and Munoz, 2011) and is applicable to watersheds <13 km$^2$. The model is spreadsheet based (Microsoft Office Excel 2003 or later) whose inputs include storm characteristics, watershed soil and cover (to calculate runoff depths), timing parameters (related to time of concentration), and unit hydrograph selection. The outputs include a calculated hydrograph and peak runoff (Hawkins and Munoz, 2011).

### *TR-55*

TR-55 is typically run for small watersheds (<65 km$^2$) and is capable of accommodating up to 10 homogenous subbasins. The model calculates storm runoff volume, peakflow rate, hydrograph, and storage volume for stormwater management (U.S. Department of Agriculture, Natural Resources Conservation Service, 2009). Storm data required by TR-55 include: rainfall return period [year], 24-h rainfall amount [inch], and rainfall distribution type (function of rainfall intensity). The TR-55 uses the Muskingum-Cunge for routing with time of concentration manually inputted or calculated using the following parameters: length [ft], slope [ft/s], surface (Manning's n), and velocity [ft/s], for sheet, shallow concentrated, and channel flow types. Using the NOAA Atlas of precipitation to determine 24-h storm depths for each recurrence interval, the TR-55 outputs corresponding peak streamflow values.

### *HEC-HMS*

The HEC-HMS is a modular framework developed by the USACE. The CN is one of several available methodologies that can be used to simulate precipitation-runoff processes based on physiographic data within watershed systems. The model can be used to simulate observed events over a system (user-defined meteorological forcing) or to simulate predefined design storms. The HEC-HMS has a more complex graphical user interface (GUI) interface than other tested models; however, the modeling framework includes options for numerous physical configurations of a watershed (subbasin, reach, junction, etc.), subbasin loss methods (SCS CN selected for this study), runoff transformation methods (SCS unit hydrograph selected), and open-channel routing methods (Muskingum-Cunge selected) (U.S. Army Corps of Engineers, 2010). The HEC-HMS model also has options to include base flow in runoff prediction.

### *Post-Fire Modifiers*

To simulate post-fire conditions, model parameters are adjusted to reflect changes in watershed properties.

**Rowe Countryman and Storey.** LUTs for the RCS method incorporate post-fire peak flow and erosion rates for time intervals up to 70 years after fire.

**USGS Linear Regression Equations.** The USGS uses estimated modifiers to scale pre-fire runoff values to post-fire runoff values (Foltz *et al.*, 2009). The modifier is a function of the soil burn severity and a parameter that accounts for increased runoff. The pre-fire $Q_n$ is then multiplied by the modifier to produce an estimate of post-fire runoff for each return interval. There are no standard guidelines to determine post-fire modifiers; BAER team members utilize their own methods, varying by region, model, or modeler (Foltz *et al.*, 2009). For this study, the modifier is calculated using Foltz *et al.* (2009):

$$\text{Modifier} = 1 + \left[(\%\text{RO}_{\text{increase}}) * \frac{(A_{\text{H}} + A_{\text{M}})}{A_{\text{T}}}\right], \quad (9)$$

where $A_{\text{H}}$ is the area of high soil burn severity [mi$^2$], $A_{\text{M}}$ is the area of moderate soil burn severity [mi$^2$], $A_{\text{T}}$ is the total watershed area [mi$^2$], and $\%\text{RO}_{\text{increase}}$ is the percent of runoff increase, post-fire [%].

Methods for estimating the %RO increase for the post-fire year have not been well defined. In the current study, the %RO increase is estimated using long-term (over 40 years) streamflow records, BAER reports, or previously published studies (Benavides-Solorio and MacDonald, 2001; Biddinger *et al.*, 2003; Brandow *et al.*, 2003). Regional watersheds with pre- and post-fire discharge records (Frye Creek, Arizona (USGS gage 9460150), Arroyo Seco, California (USGS gage 11098000), Devil Canyon, California (USGS gage 11063680), and Andrews Creek, Washington (USGS gage 12447390)) were used to estimate a %RO parameter. The *a priori* estimation of the %RO parameter has significant influence on the final post-fire modifier and poor definition of this value ultimately results in higher uncertainty in post-fire predictions. Reducing the uncertainty in the modifier is outside the scope of this study, but is a subject for future investigation.

**Curve Number Models.** To adjust the CN parameter for post-fire land cover conditions, the following guidelines (Higginson and Jarnecke, 2007) are utilized (note that the maximum CN value is 100):

$$\text{Low soil burn severity CN} = \text{pre-fire CN} + 5 \quad (10)$$

$$\text{Moderate soil burn severity CN} = \text{pre-fire CN} + 10 \quad (11)$$

$$\text{High soil burn severity CN} = \text{pre-fire CN} + 15 \quad (12)$$

The adjusted post-fire CN decreases the time of concentration parameter, resulting in faster routing of peak discharge through the affected basins.

## DATA SOURCES AND PARAMETERS

A range of parameters are necessary for pre- and post-fire model development. These parameters are often estimated using various methods (regional topographic maps, geospatial data, local knowledge, etc.) and implemented into models to predict peak flow events. This study employs and advocates electronic databases that provide objective and readily accessible tools for the acquisition of relevant model parameters. A Digital Elevation Map (DEM) can be utilized to determine contributing watershed area, basin geophysical characteristics (slope, slope aspect, or lengths), and stream features, and are acquired from the USGS (http://viewer.nationalmap.gov/viewer/). Land cover classification is used to estimate pre-fire land cover and is provided by the USGS (http://www.mrlc.gov/finddata.php). National Land Cover datasets (2001 and 2006) are 16-class land cover products across the U.S. with 30-m spatial resolution. The classification is developed from the unsupervised Landsat Enhanced Thematic Mapper+ (ETM+) satellite data. The USDA NRCS provides a Web Soil Survey for the contiguous U.S. (http://websoilsurvey.nrcs.usda.gov/app/HomePage.htm). NRCS hydrologic soil groups are used to establish a soil's associated runoff CN to define model infiltration parameters and the partitioning between incoming precipitation and surface runoff.

Soil burn severity, required for post-fire CN adjustment, is a representation of the boundary and degree of burn within a wildfire (Key and Benson, 2004). Digital soil burn severity maps are typically generated from remote-sensing products such as Landsat and are validated *in situ* by BAER teams. The validated maps are known as Burned Area Reflectance Classification (BARC) maps and can be acquired from a remote-sensing database developed by the USDA Forest Service Remote Sensing Applications Center (RSAC) (http://www.fs.fed.us/eng/rsac/baer/).

Mean annual precipitation in this study was estimated from local climate and weather stations accessible in the National Climate Data Center database (http://gis.ncdc.noaa.gov/map/viewer/#app=cdo). All study models require representation of precipitation amount, frequency, intensity, or duration. Alternatively, a design storm or a representation of the variation of precipitation depth over time can be used. The National Oceanic and Atmospheric Administration (NOAA) and National Weather Service (NWS) provide the NOAA Precipitation Frequency Estimates at various durations (i.e., 5 min, 10 min, 24 h, weekly, etc.) and recurrence intervals (i.e., 1, 2, 5, 10 years, etc.) for the U.S. with 90% confidence intervals (searchable by location coordinates at http://hdsc.nws.noaa.gov/hdsc/pfds/index.html).

## MODEL APPLICATION

Model evaluation was undertaken for eight basins in the western U.S. for both pre- and post-fire conditions; four of the basins have pre-fire observational USGS peak discharge (Table 3). The study sites are located within Arizona, California, Colorado, Montana, and Washington and provide a range of hydroclimatic conditions and varying soil burn severity distribution (Tables 3 and 4). Basin sizes range from 0.03 to 57 km$^2$ (Table 3). Frye Creek in southern Arizona was burned by the 2004 Gibson-Nuttall Complex. Southern California sites include the 2003 Old Fire in the San Bernardino Mountains (Devil Canyon) and the 2009 Station Fire in the San Gabriel Mountains (Arroyo Seco). The Northern California sites were burned by the 2010 Bull Fire in southern Sequoia (Bull #3) and the 2008 Butte Lightning Complex (Rock Creek). Andrews Creek in Washington was burned by the 2003 Fawn Peak Complex. Two smaller basins in Colorado and Montana are analyzed in this study and referred to by the name of the fire that completely burned them (Fridley, 2001 and Hayman, 2002). The Arroyo Seco is modeled both as lumped and distributed systems with the HEC-HMS model to better represent this larger basin. The three Arroyo Seco subbasins for the distributed model are AS* — Little Bear, AS* — Lower, and AS* — Colby (Table 4).

## MODEL CALIBRATION

Pre-fire models were calibrated to improve peak flow estimations where data were available. Only models whose parameters allow for adjustment are calibrated (TR-55 and HEC-HMS). Parameters dependent on the CN are adjusted to better match pre-fire observations using statistics and visual inspection of hydrographs. Calibration efforts focus primarily on matching peak discharge, with a secondary focus on discharge volume. The TR-55 is calibrated by adjusting the CN until the peak discharge matches observations for each recurrence interval, whereas the HEC-HMS model is calibrated by adjusting the CN, $I_a$, and lag time for selected pre-fire storms (hydrographs) with 15-min USGS discharge (Table 5). Adjusting the CN also alters the post-fire $T_c$ (Equations 1 and 4) and affects the volume and timing of discharge. The calibrated pre-fire models are then adjusted for post-fire conditions using Equations 10-12.

We assess pre-fire model performance for both calibrated and uncalibrated models using flood frequency information from gaged watersheds. The Weibull method is commonly used to analyze streamflow and estimate expected frequency of flows based on the assumption that peak discharge is evenly distributed over a long period of time (Pramanik *et al.*, 2010). The generated discharge values for each recurrence event are considered a reasonable approximation of the associated probability density of discharge values in a basin and allow comparison of modeled design storm simulations to an "observed" storm frequency (Clarke, 2002; Pramanik *et al.*, 2010). In the current study, a Weibull frequency distribution is generated using the observed peak flow values for basins where long-term peak discharge exists (Andrews Creek [43-year record], Arroyo Seco [98-year record], Devil Canyon [90-year record], and Frye Creek [33-year record]).

To evaluate performance, we utilize two commonly used metrics, root mean square error (RMSE), and percent bias:

$$\text{Root mean square error} = \frac{\sqrt{\sum_{i=1}^{n}\left(Q_{\text{model}} - Q_{\text{obs}}\right)^2}}{n}, \tag{13}$$

where $n$ is the number of $Q_{\text{pk}}$ events for each model.

$$\text{Percent bias} = \frac{Q_{\text{model}} - Q_{\text{obs}}}{Q_{\text{obs}}} * 100\%, \tag{14}$$

where $Q_{\text{model}}$ is the modeled discharge at a specific recurrence interval, and $Q_{\text{obs}}$ is the observed discharge (either Weibull).

## RESULTS AND DISCUSSION

### *Pre- and Post-Fire Peak Discharge*

Models are applied to the eight study basins considering model and regional constraints (Table 6). Models are initially run uncalibrated and for pre-fire conditions and then adjusted for post-fire prediction using modifiers or established methods. We also undertake calibration for the Arroyo Seco and Devil Canyon basins, where 15-min discharge is available, and use the calibrated models to predict post-fire runoff. Pre- and post-fire modeled peak discharge for 2-, 5-, 10-, 25-, and 50-year (Q2, Q5, Q10, Q25, and Q50) recurrence intervals are normalized by basin area to evaluate performance across all eight study basins.

TABLE 3. General Basin Characteristics, Including Nearest City/State, Fire Name and Year, Latitude and Longitude of Basin Outlet, Area, Outlet Elevation, Basin Slope, and Dominant Pre-Fire Vegetation (arranged by basin size).

| Study Site | Location; Nearest City | Fire, Year | Outlet (°latitude, °longitude) | Area (km$^2$) | Outlet Elevations (m) | Slope (%) | Pre-Fire Dominant Vegetation | Soil Burn Severity (%) |
|---|---|---|---|---|---|---|---|---|
| Andrews Creek[1] | Northern Washington; Mazama | Fawn Peak Complex, 2003 | 48.823, −120.146 | 57 | 1,304 | 15 | Forest/shrubland[2] | 13 (L)<br>22 (M)<br>14 (H) |
| Arroyo Seco[1] | Southern California; La Canada | Station, 2009 | 34.222, −118.177 | 40 | 426 | 6 | Shrubland/forest[3] | 14 (L)<br>66 (M)<br>13 |
| Devil Canyon[1] | Southern California; San Bernardino | Old, 2003 | 34.208, −117.331 | 14 | 634 | 15 | Shrubland/forest[2] | 6 (L)<br>31 (M)<br>63 (H) |
| Frye Creek[1] | Southern Arizona; Thatcher | Gibson-Nuttall Complex, 2004 | 32.744, −109.838 | 10 | 1,696 | 22 | Forest[2] | 25 (L)<br>42 (M)<br>20 (H) |
| Bull #3 | Southern Sequoia, California; Kernville | Bull, 2010 | 35.835, −118.46 | 4.12 | 893 | 26 | Shrubland/forest[3] | 13 (L)<br>68 (M)<br>3 (H) |
| Rock Creek | Northern California; Storrie | Butte Lightning Complex, 2008 | 39.905, −121.345 | 0.69 | 578 | 45 | Shrubland/forest[3] | 40 (L)<br>40 (M)<br>1 (H) |
| Fridley | Southern Montana; Emigrant | Fridley, 2001 | 45.51, −110.78 | 0.13 | 1,930 | 43 | Shrubland/herbaceous[2,3] | 0 (L)<br>0 (M)<br>100 (H) |
| Hayman | Central Colorado; Woodland Park | Hayman, 2002 | 39.18, −105.36 | 0.03 | 2,440 | 33 | Forest[2] | 0 (L)<br>0 (M)<br>100 (H) |

Notes: L, low; M, medium; H, high.
[1]Denotes available observational pre-fire USGS peak discharge.
[2]Homer *et al.*, 2004 (National Land Cover Database, 2001).
[3]Fry *et al.*, 2011 (National Land Cover Database, 2006).

TABLE 4. Summary of % Runoff (RO) for USGS Linear Regression Post-Fire Modifiers, Rainfall Distribution Type, Pre- and Post-Fire CN Model Parameters Used in the Wildcat5, TR-55, and HEC-HMS Models.

| | | | | Pre-Fire | | Post-Fire | |
|---|---|---|---|---|---|---|---|
| **Watershed** | **Percent RO** | **Rainfall Distribution** | **Hydrologic Soil Type** | **CN** | **$T_c$ (h)** | **CN** | **$T_c$ (h)** |
| Andrews Creek | 34 | Type I | B | 59 | 5.51 | 64 | 4.85 |
| Arroyo Seco | 50 | Type I | C | 72 | 5.14 | 81 | 3.94 |
| AS — Little Bear | N/A | | D | 71 | 1.99 | 78 | 1.63 |
| AS — Lower | N/A | | C | 73 | 4.33 | 81 | 3.41 |
| AS — Colby | N/A | | C | 73 | 2.69 | 80 | 2.19 |
| Devil Canyon | 121 | Type I | C | 73 | 2.09 | 86 | 1.39 |
| Frye Creek | 83 | Type II | B | 58 | 2.61 | 66 | 2.13 |
| Bull #3 | 147 | Type IA | D | 82 | 0.49 | 90 | 0.37 |
| Rock Creek | 66 | Type IA | D | 79 | 0.33 | 85 | 0.27 |
| Fridley | 100 | Type II | B | 74 | 0.17 | 89 | 0.11 |
| Hayman | 20 | Type II | D | 79 | 0.14 | 94 | 0.08 |

Note: AS indicates one of three subbasins of the Arroyo Seco used in the distributed models.

TABLE 5. Uncalibrated (Uncal) and Calibrated (Cal) Parameters for Arroyo Seco Lumped and Distributed Models (the distributed model consists of three subbasins denoted with AS). Storm 1 and Storm 2 identify the storms utilized in this study.

| **TR-55** | **Type** | **CN** | **$T_L$ (h)** | **$T_c$ (h)** | **$I_a$ (cm)** |
|---|---|---|---|---|---|
| Lumped | Uncal | 72 | — | 5.14 | — |
| | Cal | 51 | — | 6.80 | — |
| **HEC-HMS** | **Type** | **CN** | **$T_L$ (h)** | **$T_c$ (h)** | **$I_a$ (cm)** |
| Lumped | Uncal | 72 | 6.17 | 10.28 | 0.99 |
| | Cal storm 1 | 45.5 | 3.17 | 5.28 | 10.39 |
| | Cal storm 2 | 35.25 | 5.25 | 8.75 | 10.80 |
| AS — Colby | Uncal | 73 | 1.61 | 2.69 | 1.88 |
| | Cal storm 1 | 21 | 2.08 | 3.47 | 8.13 |
| | Cal storm 2 | 21 | 2.33 | 3.89 | 7.87 |
| AS — Little Bear | Uncal | 71 | 1.19 | 1.99 | 2.08 |
| | Cal storm 1 | 21 | 2.67 | 4.44 | 7.62 |
| | Cal storm 2 | 21 | 1.67 | 2.78 | 7.87 |
| AS — Lower | Uncal | 73 | 2.59 | 4.32 | 1.88 |
| | Cal storm 1 | 21 | 6.67 | 11.11 | 8.13 |
| | Cal storm 2 | 21 | 3.75 | 6.25 | 7.87 |

Uncalibrated model predictions across the sites (peak discharge/unit area) are highly variable under both pre- and post-fire conditions (Figures 1 and 2). For pre-fire conditions, the models underpredict the estimated peak discharge for Q2-Q10 at Andrew Creek (Figure 1a) and improve for the larger events in this basin. Pre-fire CN models (TR-55 and HEC-HMS) at Arroyo Seco (Figure 1c) and Devil Canyon (Figure 1e) overpredict for each peak discharge event. The USGS model also overpredicts at the Q25 and Q50 events. However, the RCS model performs well across the events when compared to the observed (Weibull estimate) peak discharge. Pre-fire model predictions at Frye Creek (Figure 1g) have the best consistency when compared to the observed peak discharge. Pre-fire models at the Bull #3 (Figure 2a), Rock (Figure 2c), Fridley (Figure 2e), and Hayman (Figure 2g) sites show increasing variability between predictions at each recurrence interval, with more spread observed for the larger peak discharge events.

The uncalibrated post-fire models show the most discrepancy in peak discharge predictions (Figures 1 and 2). In general, the smaller and steeper basins (Bull #3, Fridley, and Rock Creek) generate more discharge per unit area (Figure 2). Andrews Creek is the largest basin with the least amount of burned area relative to all study sites and produces the least amount of discharge per unit area (Figures 1a and 1b). The RCS peak discharge predictions are based on *in situ* observational data, reducing the uncertainty in post-fire values. The RCS predictions at the lower recurrence intervals (Q2-Q10) correspond well to the USGS regression model (Figures 1d-1f). The USGS regression performs well in the lower recurrence intervals pre-fire providing more confidence in post-fire prediction. The Wildcat5 generally has simulations in the middle of the ensemble of predictions, suggesting better overall performance relative to the other models (Figures 1f and 2d-2f). At Fridley and Hayman, the TR-55 is highly incongruous with the other models (Figures 2f and 2h). At Rock Creek, all the CN models are inconsistent with the USGS regression model (Figure 2d). The inconsistency between model predictions, especially notable in the smaller watersheds, contributes to the uncertainty in model prediction and highlights the discretion necessary for model selection.

### *Curve Number Model Parameter Sensitivity*

Simulated peak discharge (per unit area) appears strongly influenced by watershed characteristics but shows significant variability between models

TABLE 6. Available Pre- and Post-Fire Models for Each Basin, Where [1] Indicates Observational Data that Are Available for Pre-Fire Model Calibrations and * Indicates Calibrated Pre-Fire Models and Post-Fire Models Adjusted from the Calibrated Pre-Fire Models.

| Model | RCS | USGS Linear Regression | TR-55 | Wildcat 5 | HEC-HMS |
|---|---|---|---|---|---|
| Andrews Creek[1] | — | Pre, Post | Pre, Post | — | Pre, Post |
| Arroyo Seco[1] | Pre, Post | Pre, Post | Pre, Post | — | Pre, Post |
| | | | Pre*, Post* | | Pre*, Post* |
| Devil Canyon[1] | Pre, Post | Pre, Post | Pre, Post | — | Pre, Post |
| | | | Pre*, Post* | | Pre*, Post* |
| Frye Creek[1] | — | Pre, Post | Pre, Post | Pre, Post | Pre, Post |
| Bull #3 | — | Pre, Post | Pre, Post | Pre, Post | Pre, Post |
| Rock Creek | — | Pre, Post | Pre, Post | Pre, Post | Pre, Post |
| Fridley | — | Pre, Post | Pre, Post | Pre, Post | Pre, Post |
| Hayman | — | Pre, Post | Pre, Post | Pre, Post | Pre, Post |

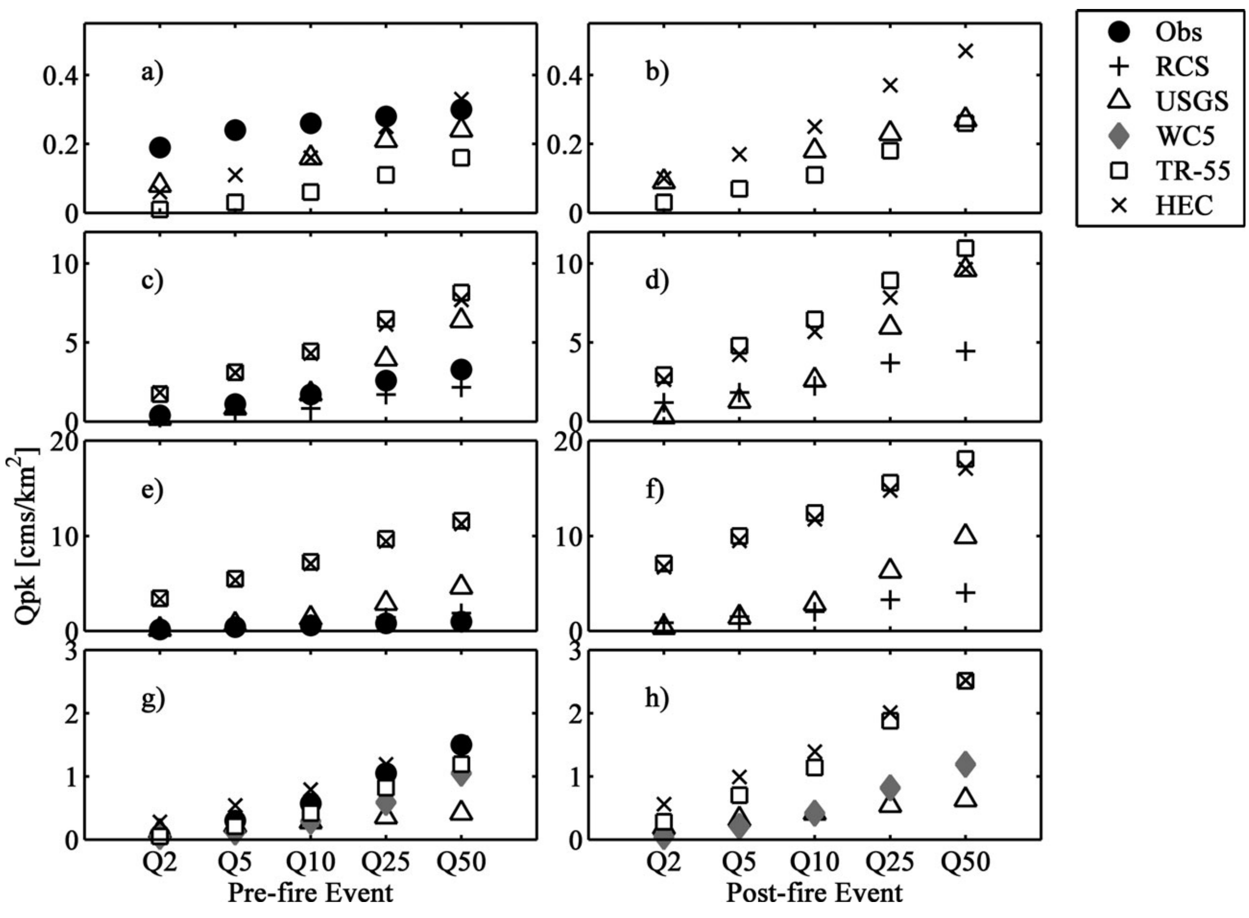


FIGURE 1. Variability of Modeled Peak Discharge per Unit Area Pre- and Post-Fire for Study Basins with Observational Data: Andrews Creek (a and b), Arroyo Seco (c and d), Devil Canyon (e and f), and Frye Creek (g and h).

(Figure 3). The TR-55 is highly sensitive to model parameters. Slope (Figure 3b), soil type (Figure 3e), and CN (Figure 3f) have the most influence on pre-fire model CN predictions. In the CN models, slope influences the time of concentration; with steeper slopes equating to smaller residence time within the basin. The shorter time of concentration values produce more immediate discharge, especially under post-fire conditions. Under post-fire conditions, the CN (Figure 3m) and percent of the basin burned (Figure 3o) have significant influence on modeled discharge. Rainfall distribution, determined by site location and used as input to the USGS and CN models, also influences the predicted discharge. Some of the

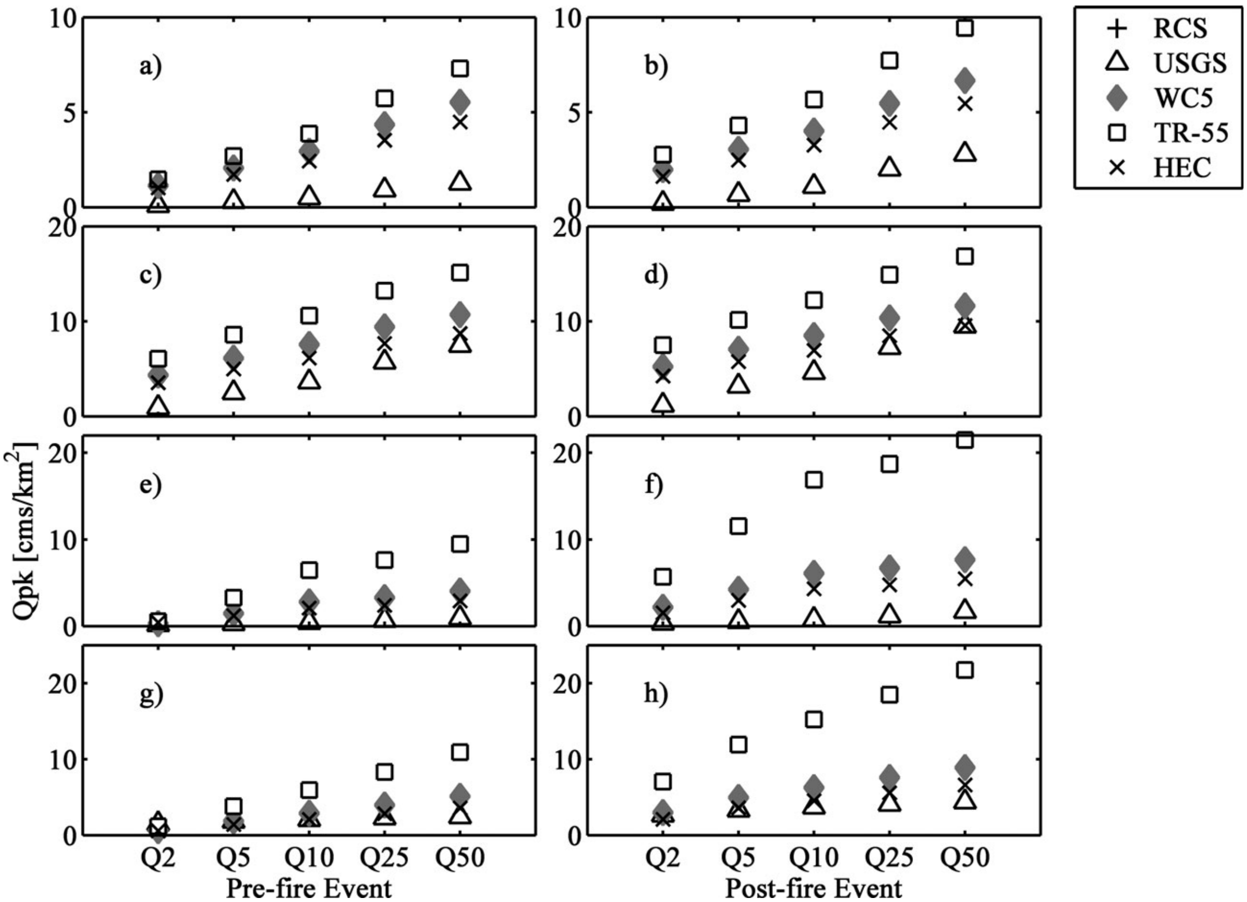


FIGURE 2. Variability of Modeled Peak Discharge per Unit Area Pre- and Post-Fire for Study Basins without Observational Data: Bull #3 (a and b), Rock Creek (c and d), Fridley (e and f), and Hayman (g and h).

California watersheds are on the boundary between NRCS Types I and IA rainfall distribution types. The Type IA rainfall distribution (Bull #3) results in a larger runoff response. This is extremely pronounced in the Q25, Q50 during pre-fire conditions, and for all post-fire events (Figures 1e and 1f). Similarly, the CN significantly influences the overall volume of predicted runoff. We note that both rainfall type and CN are relatively subjective and contribute to model uncertainty due to the inconsistencies in CN acquisition and rainfall distribution type.

Soil classification appears to have more influence on post-fire discharge (Figure 3l). However, this is mostly noted in the HEC model where interactions with other routing parameters may be influencing post-fire discharge. The California and Hayman sites are generally characterized by soil types C (Arroyo Seco and Devil Canyon) and D (Bull Fire, Hayman, and Rock Creek), which generate moderate and high runoff potential, respectively. In both soil groups, C and D, water transmission is restricted. Fridley and Frye Creek are characterized by soil type B, defined as moderately low runoff potential and unimpeded water transmission. Under immediate post-fire conditions, most surface soils are hydrophobic to some degree which contributes to increased runoff. Breakdown of the hydrophobic layer is dependent on amount and intensity of rainfall (De Bano, 2000) and can be represented by CN alteration. Post-fire CN models are sensitive to soil parameters and can be modified (Higginson and Jarnecke, 2007; Cydzik and Hogue, 2009; Chen *et al.*, 2013) to reflect an increase in immediate surface runoff and a decrease in infiltration.

### *Calibration*

The lumped and distributed Arroyo Seco design for the HEC-HMS model result in distinct differences in both uncalibrated and calibrated parameters (Table 5). The CN significantly decreases and the initial abstractions significantly increase in both the calibrated lumped and distributed models, as a result of having to lower the water volume to match basin rainfall-runoff response. The alteration in CN and

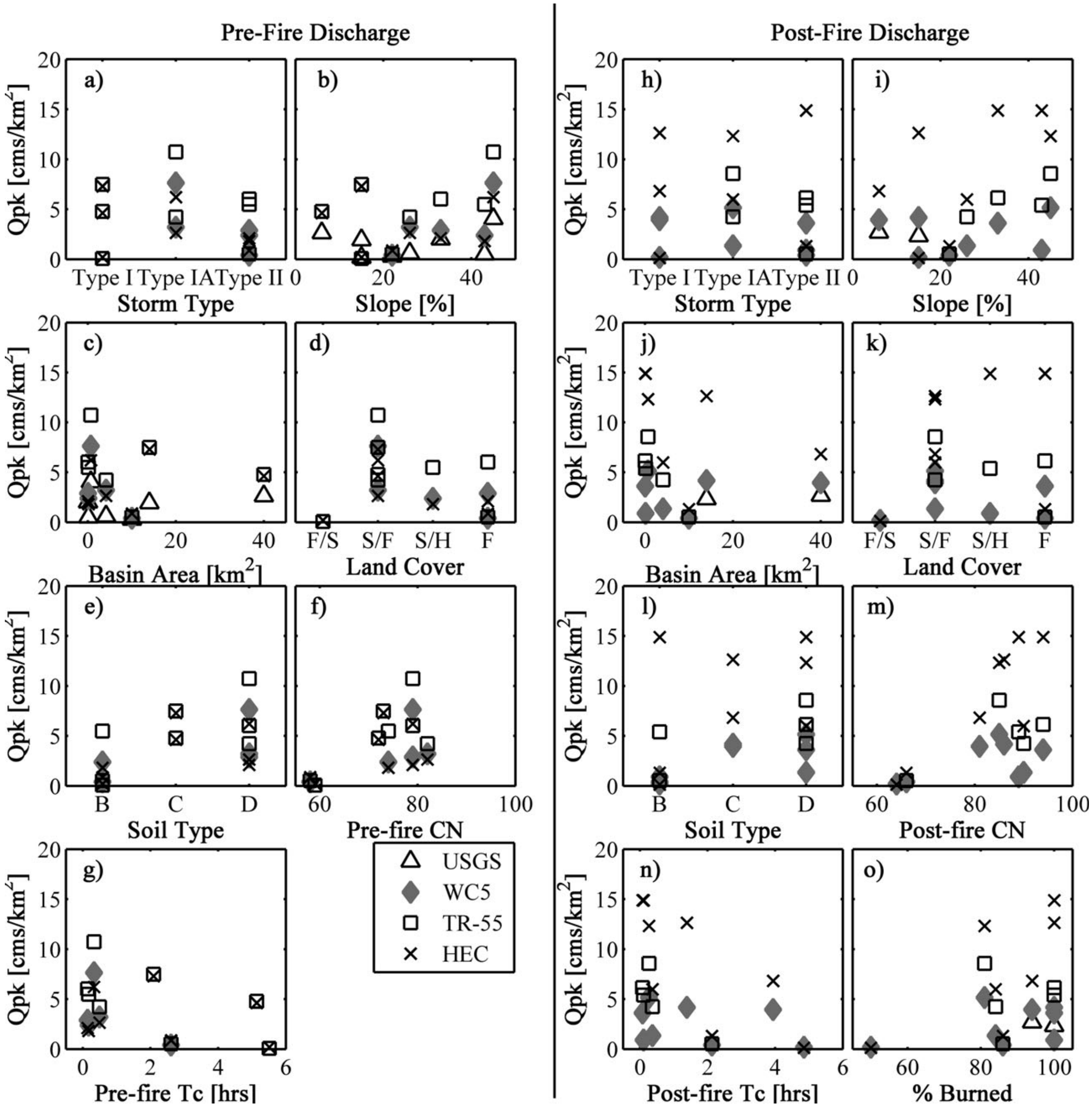


FIGURE 3. Pre- and Post-Fire Peak Discharge per Unit Area with Respect to Model Variables. Storm Type (a and b) is from the NRCS Rainfall Distribution Types. Land Cover (d and k) is from the USGS National Land Cover datasets (2001 and 2006), where "F/S" is predominantly forest and shrubland, "S/F" is predominantly shrubland and forest, "S/H" is predominantly shrubland and herbaceous, and "F" is predominantly forest. The hydrologic Soil Type (e and l) is from the USDA Natural Resources Conservation Services Web Soil Survey.

initial abstraction reflects sensitivity to soil type and land cover, which govern the transmission of runoff into the soil.

The lag time for the lumped Arroyo Seco and Lower Arroyo Seco subbasin are also lowered to route water more quickly from the upper parts of the basin to the outlet, which more appropriately accounts for the steepness of the watershed (Table 5). The lumped and distributed simulations for two observed storms in the Arroyo Seco (Storm 1: 24-28 December 2003 and Storm 2: 19-26 October 2004) show significant improvement after calibration (Figures 4b and 4d [uncalibrated] *vs.* Figures 4a and 4c [calibrated]). The observed discharge is greatly overestimated by the uncalibrated lumped and uncalibrated distributed hydrographs for each storm (Figures 4a and 4c). The calibrated distributed model is better able to capture the peak and volume of the observed storm than the lumped model. The October 2004 storm, which has a dual peak, had simulations that did not adequately

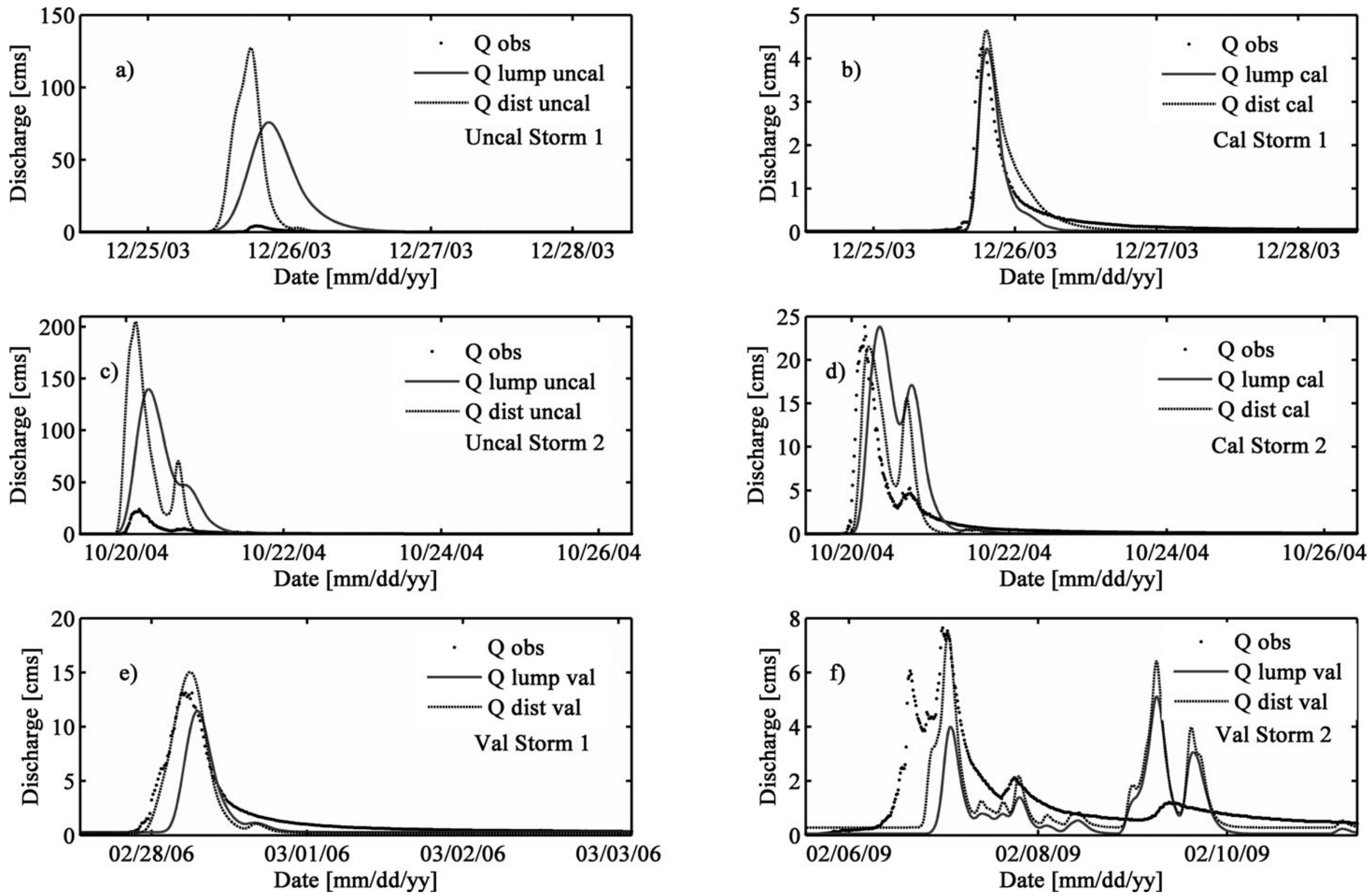

FIGURE 4. Uncalibrated (a and c) and Calibrated (b and d) HEC-HMS Lumped and Distributed Hydrographs for Two Pre-Fire Observed Storms in the Arroyo Seco, 25-28 December 2003 (Storm 1) and 20-26 October 2004 (Storm 2). Two Validation Storms for Arroyo Seco HEC-HMS lumped and distributed models (e and f) for 28 February-3 March 2006 (Val Storm 1) and 6-10 February 2009 (Val Storm 2).

match the observed discharge (Figure 4d). The second pulse of precipitation is difficult to capture, and both models overpredict discharge response. Overall, the distributed calibrated model performs better than the lumped calibrated model (Figure 4d).

The final calibrated parameters are next evaluated on two independent storm events (Figures 4e and 4f). Simulations generally result in adequate performance for the lumped and distributed models for 28 February-3 March 2006 (Val Storm 1) (Figure 4e). A less successful validation is highlighted for a storm occurring 6-11 February 2009 (Val Storm 2) (Figure 4f). Both storms indicate that both TR-55 and HEC-HMS are sensitive to precipitation volumes and intensity, which is influenced by the initial abstraction parameter in the model. Overall, the distributed model performs better than the lumped model, demonstrating the influence of including parameter variability throughout the basin. The calibrated models are used to predict pre- and post-fire discharge for Arroyo Seco (Figures 5a and 5b) and Devil Canyon (Figures 5c and 5d). For pre-fire, the calibrated peak discharge is significantly less than the uncalibrated discharge (Figures 5a-5c). The calibrated models also generally perform better for Devil Canyon (Figure 5c) than in the Arroyo Seco (Figure 5a). Uncalibrated models predict significantly more peak discharge post-fire, and calibrated TR-55 and HEC-HMS models are more consistent with the RCS and USGS methods (Figures 5b-5d).

### *Model Uncertainty and Errors*

Model errors are highly variable across all basins and fire sites (Figure 6). Study models applied to Andrews Creek generally undersimulate (−435 to −38% bias) (Figure 6a). The uncalibrated Q25 HEC-HMS (−15%), uncalibrated Q50 HEC-HMS (14%), and Q50 USGS (−22%) are better and have lower percent bias values (Figure 6a). The uncalibrated TR-55 and HEC-HMS models at the Arroyo Seco site have large positive bias, ranging from 133 to 611% (Figure 6b). The RCS method undersimulates at the Arroyo Seco

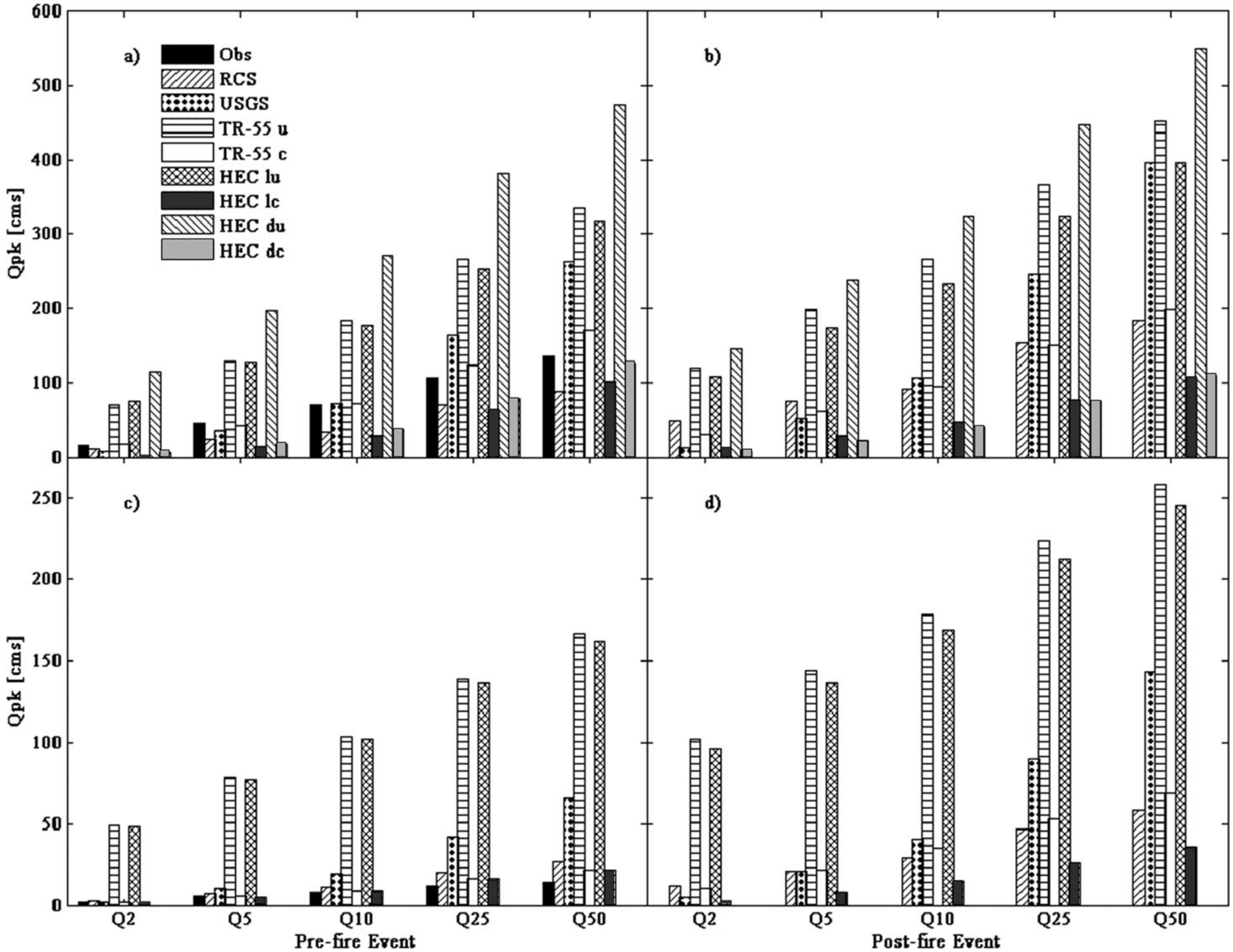


FIGURE 5. Arroyo Seco (a and b) and Devil Canyon (c and d) Pre- and Post-Fire Estimated Peak Discharge per Unit Area for Applicable Models (RCS, USGS, TR-55, and HEC). For these basins, TR-55 and HEC include uncalibrated (u) or calibrated (c) models.

(−52 to −34%), while bias in the USGS model ranges from −48 to 94%, showing overprediction in the higher recurrence intervals (Figure 6b). The calibrated TR-55 at the Arroyo Seco shows some of the best performance, with percent bias ranging from −7 to 26% across all events. The lumped and distributed calibrated HEC-HMS models have larger negative bias, ranging from −82 to −7% (Figure 6b). Models at Devil Canyon have the largest spread of percent bias values primarily due to the uncalibrated TR-55 and HEC-HMS predictions (over 1000% bias) (Figure 6c). The RCS results in bias values from 25 to 88%, where Q25 and Q50 have higher positive bias. The USGS method has lower bias for only the Q2 event (Figure 6c). The calibrated TR-55 and HEC-HMS models significantly reduce percent bias for all discharge recurrence intervals in Devil Canyon, especially the Q2 through Q25 events (Figure 6c). Models applied to Frye Creek generally show negative bias (Figure 6d), with the USGS ranging from −79 to 28%, and showing the best performance at Q5 (Figure 6d). The Wildcat5 shows the tightest percent bias range (−33 to −5%) for all peak discharge events, even though it is an uncalibrated model (Figure 6d).

Where observational data are available, the mean RMSE for each applicable model for Andrews Creek, Arroyo Seco, Devil Canyon, and Frye Creek is computed. The aggregate RMSE value highlights the overall tendency of models to under or overpredict peak discharge across the range of recurrence intervals (Figure 7). The uncalibrated TR-55 and HEC-HMS have significantly larger error than all available models at each site (Figure 7). The TR-55 generally has a lower model error than the HEC-HMS (Figures 7b-7d). Andrews Creek and Frye Creek have the lowest RMSE across all models (Figures 7a-7d).

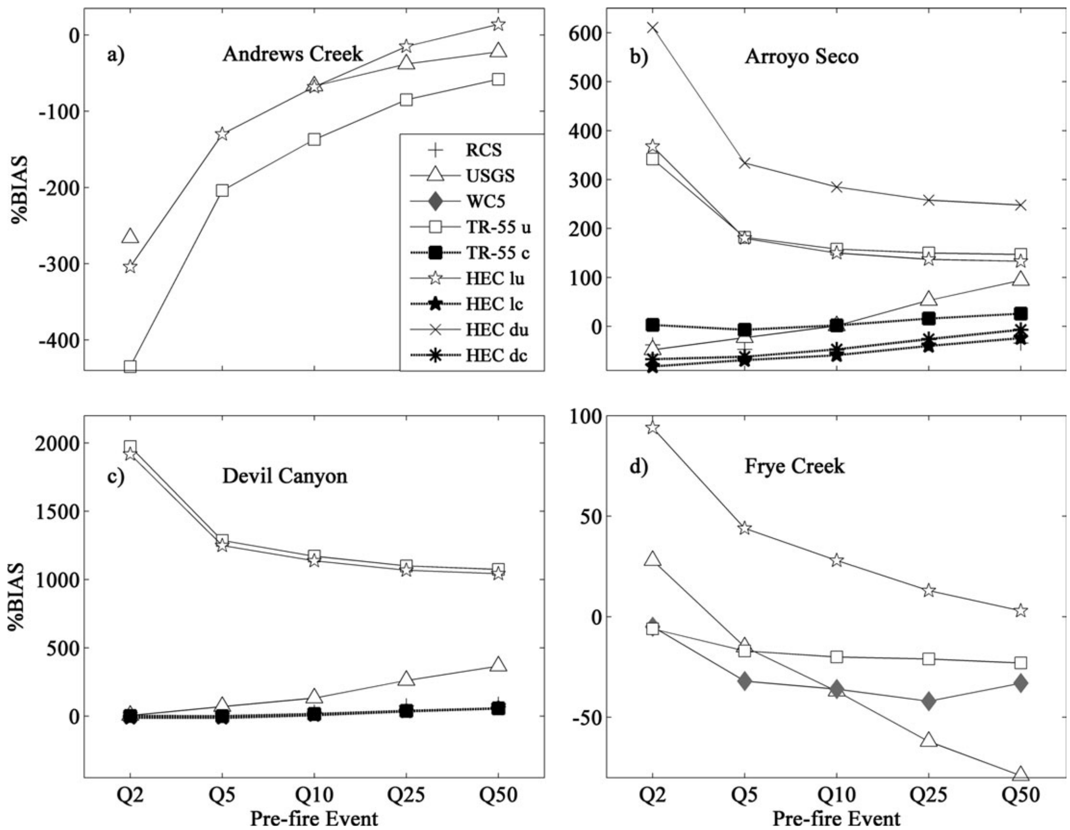


FIGURE 6. Percent Bias for Pre-Fire Andrews Creek (a), Arroyo Seco (b), Devil Canyon (c), and Frye Creek (d) Models Relative to Observational Data for Each Peak Discharge Event.

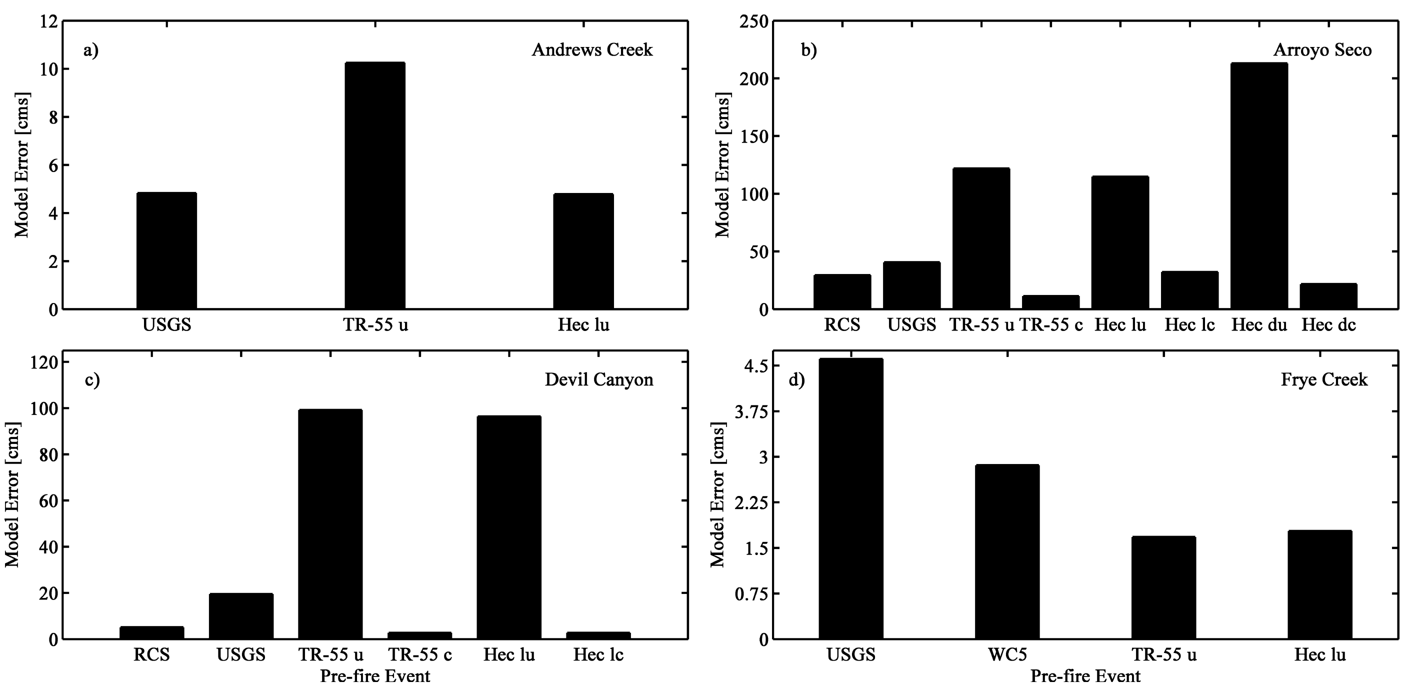


FIGURE 7. Andrews Creek (a), Arroyo Seco (b), Devil Canyon (c), and Frye Creek (d) Model Error Across All Peak Discharge Events for Available Pre-Fire Models with Observational Data, where "u" Are Uncalibrated, "c" Are Calibrated, "l" Are Lumped, and "d" Are Distributed Models.

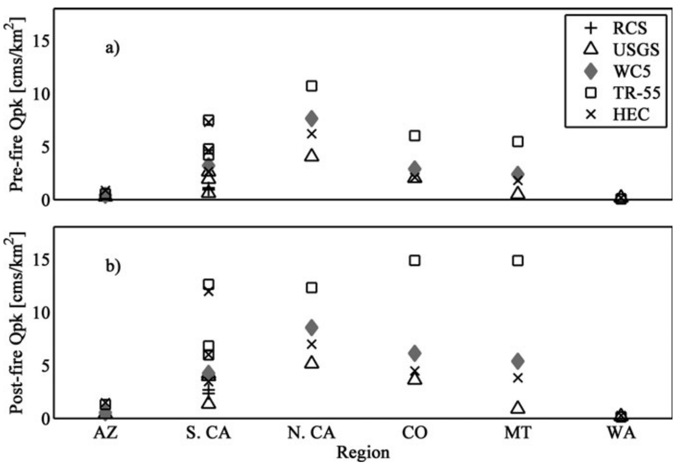


FIGURE 8. Pre- and Post-Fire (a and b) Mean Peak Discharge per Unit Area for All Models by Region (Arizona (AZ), Southern California (S. CA), Northern California (N. CA), Colorado (CO), Montana (MT), and Washington (WA)).

The mean of all the peak discharge predictions at each site by region highlights overall consistency of model performance (Figure 8). The TR-55 model shows the least consistent performance relative to other applicable models, especially in southern California, northern California, Colorado, and Montana (Figures 8a and 8b). The highest consistency between the pre- and post-fire model predictions occurs for sites in Arizona and Washington (Figures 8a and 8b). The largest discrepancy is observed for northern California and for post-fire southern California, Colorado, and Montana (Figure 8). There is less agreement between post-fire models for southern California, northern California, Colorado, and Montana (Figure 8b).

## CONCLUSIONS

The current study involves systematic evaluation of a range of models commonly used in post-fire hydrologic assessments, especially within the operational community. We advocate the implementation of standardized methods to acquire model parameters and transferability of model results from this study to other regions and fires should be used with reservation. In general, results show that discharge estimates are highly variable for the studied watersheds, heavily influenced by climatology (location), geophysical properties, and soil burn severity, and that no single model appears suitable across the range of systems studied. Key insight on model performance is summarized as follows:

1. Estimated peak discharge is highly variable depending on the model and parameter selection within the system.
2. The RCS method performs well as it is based on observational data, but RCS has limited regional applicability (only available for southern California). The RCS is also a static model that is not adaptable to changing geomorphology and climate conditions.
3. The USGS linear regression model includes a subjective modifier used to adjust toward post-fire peak runoff (requires percent of runoff increase *a priori*), adding significant uncertainty in discharge estimates. The regional regression equations are broad and not fine tuned for specific watersheds, resulting in more variable performance.
4. The Wildcat5 seems to perform the best overall given current methods to acquire CN and without calibration, but application is limited by basin size.
5. The uncalibrated TR-55 tends to overestimate peak discharge events for all watersheds, and has more uncertainty during low-flow events.
6. The HEC-HMS model has a moderate learning curve due to its complex GUI and high number of required parameters, but provides good results after calibration. In addition, the HEC-HMS provides more flexibility for watershed setup (i.e., loss methods, runoff transformations, routing) with user-defined model selections and parameter input.
7. The utilized CN models are especially sensitive to CN; however, a standardized method to acquire and calibrate these models currently does not exist, increasing uncertainty in model results.

For CN models (i.e., TR-55 and HEC-HMS), we recommend that a regional basin can be used to calibrate and transfer model parameters to the basin of interest. If sufficient time and data are available to undertake calibration, we recommend the use of the HEC-HMS. The model provides the most customizable system, which if used properly, can best reflect watershed behaviors and properties. However, if calibration data or adequate time is not available, the Wildcat5 is suitable for watersheds that meet the basin size constraints. Proper selection of a model that performs well for the region of study, and can be calibrated, will ultimately improve confidence in post-fire flow predictions, reducing management costs and improving regional resource allocation.

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