Journal of Hydrology 388 (2010) 370–378

Contents lists available at ScienceDirect

Journal of Hydrology

journal homepage: www.elsevier.com/locate/jhydrol

# Streamflow response to fire in large catchments of a Mediterranean-climate region using paired-catchment experiments

Ryan Bart *, Allen Hope

*Department of Geography, San Diego State University, 5500 Campanile Drive, San Diego, CA 92182-4493, USA*

ARTICLE INFO

*Article history:*
Received 29 November 2009
Received in revised form 6 April 2010
Accepted 10 May 2010

This manuscript was handled by K. Georgakakos, Editor-in-Chief, with the assistance of Ashish Sharma, Associate Editor

*Keywords:*
Streamflow
Fire
Paired catchment
Regression
California

SUMMARY

Understanding post-fire streamflow dynamics in large California catchments is limited by a lack of direct empirical evidence. Scaling results from small experimental catchments to large catchments for practical applications is challenging. We investigated the possibility of using streamflow data from an existing gauge network in central and southern California to examine the effects of fire on streamflow using a paired-catchment approach. Post-fire streamflow change was examined in six paired catchments at annual, seasonal and monthly time-periods. Prediction intervals associated with the pre-fire calibration regression models were used to identify statistically significant changes in post-fire streamflow. The identification of suitable paired test and control catchments presented a major challenge, despite the large number of potential catchments in the network. The best calibration results were associated with catchment pairs that had similar orographic controls over rainfall, with proximity to one another being a secondary control. The effect of fires on streamflow, regardless of time-period examined, was found to be variable, depending mostly on post-fire wetness conditions. No relation was evident between post-fire streamflow change and catchment size or area burnt.

Published by Elsevier B.V.

## 1. Introduction

Fire is a common source of land-cover change in Mediterranean-Climate Regions (MCR). These regions; which occupy parts of Australia, California, Chile, the Mediterranean Basin and South Africa; are characterized by warm, dry summers and cool, wet winters. They are also known to be heavily impacted by human development and contain considerable amounts of agricultural lands, which strain the limited locally-available water supplies (Service, 2004). Fire modifies hydrologic fluxes through changes in vegetation transpiration and soil hydrophobicity (Neary and Ffolliott, 2005) and is expected to increase in frequency with predicted climate change (Lenihan et al., 2003; Moreno and Oechel, 1995; Williams et al., 2001). There is a need to understand the consequences of these changes in hydrological fluxes on catchment streamflow. This understanding is particularly needed in large (>50 $km^2$) catchments, where knowledge of streamflow regime is critical for flood control, water resource management and preservation of natural ecosystems.

Although streamflow response to fires in MCR catchments has been investigated since the 1930s (e.g. Hoyt and Troxell, 1934), streamflow response of large catchments is still unclear. Most streamflow change experiments have been conducted in small (<5 $km^2$), well-gauged experimental catchments. The results from these experiments generally indicate that streamflow increases following fire at annual and monthly time-periods (Lavabre et al., 1993; Lindley et al., 1988; Scott, 1993). However, other experiments, such as those conducted by Bosch et al. (1984) and Britton (1991) in small South African catchments, have found no increase in post-fire streamflow. Recently, a number of empirical studies have been conducted using large MCR catchments. Hessling (1999) reported that annual streamflow increased by 50% following fire in a 49 $km^2$ catchment in Cyprus. Similarly, Loáiciga et al. (2001) found annual post-fire streamflow increased by 20–30% following the examination of multiple fires in a 272 $km^2$ southern California catchment. In contrast, a study by Aronica et al. (2002) in two Sicilian catchments (76 $km^2$ and 50 $km^2$) did not identify any conclusive increases in annual or monthly post-fire streamflow. Finally, in a medium-sized southern California catchment (14 $km^2$), Jung et al. (2009) found that streamflow behavior and its response to fire can vary dramatically depending on whether the catchment is dominated by groundwater or overland flow. Overall, these studies indicate that streamflow may, or may not increase following fire; suggesting that streamflow response to fire is dependent on static and/or dynamic catchment characteristics.

A major challenge for detecting changes in streamflow following land-cover change is establishing an accurate estimate of streamflow which represents conditions of no land-cover change

* Corresponding author. Tel.: +1 619 594 8031; fax: +1 619 594 4938.
*E-mail addresses:* rbart@rohan.sdsu.edu (R. Bart), hope1@mail.sdsu.edu (A. Hope).

0022-1694/$ - see front matter Published by Elsevier B.V.
doi:10.1016/j.jhydrol.2010.05.016

(i.e. the control). Although numerous modeling approaches have been employed to evaluate land-cover change on streamflow, the most direct approach is to conduct a paired-catchment experiment. The first step in a paired-catchment experiment is the development of a regression model to predict streamflow in a test catchment from streamflow in a nearby control catchment. After vegetation has been altered in the test catchment, the regression model and data from the control catchment are used to estimate an expected streamflow for the no-change conditions. The difference between the observed and predicted streamflow in the test catchment, which is commonly attributed to the land-cover change, can then be tested for statistical significance (e.g. Scott and Van Wyk, 1990; Watson et al., 2001).

Systematic agreement between streamflow in the paired-catchment regression model is essential for accurate estimates of streamflow change. Consequently, the application of the paired-catchment approach has generally been limited to small catchments in close proximity to one another (Andréassian et al., 2003). This minimizes uncertainties in the regression model by increasing the likelihood that the test and control catchments will comply with three assumptions of the paired-catchment experiment; similarity of rainfall regime between the test and control catchment, similarity of catchment hydrological behavior, and stable land-cover conditions for the control catchment (Andréassian, 2004).

Scaling the results from small catchment experiments to large catchments remains difficult (Best et al., 2003). There is a potential for unique scale-dependent feedbacks, such as bank recharge, to be present in large catchments that may not be represented in small catchments. In addition, the proportion of catchment area hydrologically connected to the stream is likely to be smaller in large catchments than in small catchments, lessening the impact of land-cover change in those unconnected parts of the catchment (Bracken and Croke, 2007). Also, increased heterogeneity in catchment characteristics; along with a higher tendency for partial burning, create a mosaic of land parcels with unique hydrologic properties in large catchments. As a result, small-scale streamflow change experiments cannot be used to directly infer post-fire streamflow response in larger catchments.

There are two primary obstacles to implementing the paired-catchment approach using large catchments. The first obstacle involves selecting a suitable test and control catchment. While the advantage of using small, homogeneous experimental catchments is control over land-cover change and the practicality of accurately measuring catchment conditions, these types of catchments are limited in number and only represent localized conditions. Consequently, it is attractive to consider using catchments from established gauging networks that cover an entire region. While network catchments are not necessarily ideal for research purposes; they frequently represent the best and only opportunity for evaluating the effects of fire on streamflow at larger scales. The use of network gauges is inherently an opportunistic approach which is constrained by the availability of both wildfires and streamflow data. Still, the large number of potential catchments in gauging networks provides the possibility of conducting multiple catchment experiments in a region.

The second obstacle to implementing the paired-catchment approach using large catchments relates to the possible weakening of the paired-catchment assumptions as catchment area increases (Andréassian, 2004). Increases in catchment area, along with potential increases in the distance between catchment pairs, will likely reduce the similarity of catchment characteristics between the test and control catchment while contributing to diverging temporal and spatial patterns of rainfall. These changes will likely cause less systematic agreement between streamflow in the two catchments. While it is recognized that relaxing the paired-catchment assumptions may add greater calibration uncertainty and reduce the ability of the control catchment to predict post-fire streamflow in the test catchment, the exact limits of using the paired-catchment approach are unknown. It has been suggested by Loftis et al. (2001) that under certain conditions, incorporating a paired catchment to a land-cover change study can be beneficial when the coefficient of determination ($R^2$) from the paired-catchment streamflow calibration model is as low as 0.3.

Several studies implementing the paired-catchment approach for large-scale land-cover change experiments have demonstrated that satisfactory calibration models can be achieved despite potentially compromising paired-catchment assumptions. Hessling (1999) realized a $R^2$ value of 0.99 for a regression model between the annual runoff of two adjacent test and control catchments (49 $km^2$ and 39 $km^2$). Loáiciga et al. (2001) reported a $R^2$ value of 0.92 for a regression model between the annual streamflow of two paired catchments (272 $km^2$ and 559 $km^2$), despite the control catchment being located 80 km from the test catchment. In a very large (6810 $km^2$) Australian catchment, Liu et al. (2004) used a nested paired-catchment approach to try to identify changes in post-fire streamflow; however the strength of the calibration relation was not reported. These successful calibrations demonstrate that the paired-catchment approach may be suitable for use in large catchments.

## 2. Research objectives

The main objective of this study was to evaluate the effects of fire on streamflow volumes using a paired-catchment methodology and large catchments selected from an existing streamflow gauge network in central and southern California. This unique application of the paired-catchment approach follows a recommendation by Andréassian (2004) to investigate the effects of land-cover change on streamflow in large catchments using paired-catchment experiments. Despite possibly greater uncertainty associated with the relaxing of key paired-catchment assumptions, we hypothesized that: (1) paired catchments could be identified in this region that had calibration regression models suitable for identifying the effects of fire on streamflow volumes, and (2) fires which burnt greater than 25% of the catchment area would result in an increase in streamflow.

Hydrological processes affected by fires may be expected to vary over different time-periods as rainfall and energy change with season, and as catchment soils and vegetation recover to pre-fire conditions. Consequently, the paired-catchment approach was used to examine the effects of fire on streamflow measured at three time-periods: monthly, seasonal and annual. It is recognized that most paired-catchment studies are conducted at annual time-periods due to potential complications from lags in hydrological processes and variations in soil moisture storage between paired catchments at periods less than 1 year. However, the strength of the calibration relation may be used to indicate whether these lags introduce unacceptable uncertainty in the calibration model. Thus, we examined the utility of monthly and seasonal time-periods in order to evaluate two potentially dominant catchment processes associated with post-fire streamflow response that we expected to manifest at these time scales, hydrophobicity and reductions in transpiration capacity.

The impact of hydrophobicity on streamflow may be expected to be most prevalent following initial, large post-fire rainfall events since soil hydrophobicity is greatest immediately after a fire and breaks down with subsequent rainfall events (DeBano et al., 1998). Consequently, we examined differences in streamflow for the individual winter months of December, January and February, as well as the entire winter period, during the first year following fire. The early wet season months of October and November were not selected for analysis as streamflow in many of the catchments does not consistently flow during these months. Changes in transpirational capacity may be expected to have maximum impact on streamflow during the spring period when energy is increasing, soil water is available, and actual evaporation approaches potential evaporation. Therefore, a spring period defined as the months of March, April and May was examined for changes in streamflow. Finally, changes in the overall water balance were examined at the traditional annual time-period, with the water year extending from October 1 of the previous year through September 30 of the current year.

## 3. Methodology

### 3.1. Selection of catchment pairs

The United States Geological Survey (USGS) maintains an extensive network of streamflow gauges from which data is freely accessible (http://waterdata.usgs.gov/nwis). Since our focus was on evaluating streamflow change in large catchments, 231 USGS catchments with areas greater than 50 km$^2$ were identified as potential study catchments. The geographic extent of the study area extended from latitude 39°N in the north to the southern California border with Mexico. A number of quality control measures were used to ensure that the catchments were suitable for paired-catchment analysis. First, catchments were required to be in a predominately natural state, so as not to be influenced by extraneous variables that affect the timing and amount of streamflow. Thus, catchments containing significant impoundments, along with substantial water diversions, both to and from the stream, were removed from consideration. Similarly, catchments with urbanization and agriculture were also eliminated. Finally, catchments with large amounts of winter snow cover were removed, as long-term snow packs can affect the timing of streamflow, making it difficult to correlate streamflow between paired catchments.

The fire history of each of the remaining 71 catchments was characterized using a fire perimeter geographic information system (GIS) layer from the Fire and Resource Assessment Program (FRAP) (http://frap.cdf.ca.gov/). For test catchment selection, we set a requirement that fires had to exceed 25% of the catchment area. This threshold was based on a modeling study by McMichael and Hope (2007) that indicated fires below this threshold had no impact on streamflow. In addition, test catchments could not have any other significant fires (>5% of catchment area) for a minimum of 10 years before and 5 years after the fire event. Control catchments were required to have no significant fires during the 15-year period that coincided with the test catchment period.

### 3.2. Paired-regression analysis

The statistical approach used in this study was adapted from the Watson et al. (2001) approach, which identified statistically significant changes in streamflow using regression analysis with prediction intervals and an explicit consideration of statistical assumptions. Post-fire streamflow may be evaluated for significant change relative to the pre-fire regression model using one of two common techniques, the dummy variable approach or prediction intervals. The dummy variable approach assesses streamflow change by testing whether overall streamflow during the post-fire period is significantly different from streamflow during the pre-fire period (Scott and Van Wyk, 1990). Alternatively, prediction intervals around the regression line can be calculated and used as an estimate of the interval that encompasses post-fire observations unaffected by fire (Hocking, 2003). Post-fire streamflow exceeding this interval may then be attributed to land-cover change. Prediction intervals allow the ability to assess the significance of streamflow change for individual years, as opposed to the entire post-fire period as with the dummy variable approach (Sheather, 2009). The prediction interval around any streamflow response variable $y_k$ is defined as

$$P.I. = y_k \pm s\left[1 + \frac{1}{n} + \frac{(x_k - \bar{x})^2}{\sum_{i=1}^{n}(x_i - \bar{x})^2}\right]^{1/2} t_{1-\alpha/2,n-2} \quad (1)$$

where $s$ is standard deviation of the residuals, $n$ is the number of observations, $x$ is the predictor variable, and $t_{1-\alpha/2,n-2}$ is the $z$-score from a Student's $t$-distribution table (Haan, 2002). The magnitude of prediction intervals varies in proportion to the $R^2$ of the calibrated model, such that a stronger relation between the control and test catchment will likely improve streamflow change detection. In this study, we used prediction intervals at the ninety-fifth percentile (95%) to identify statistically significant changes in streamflow during the first 5 years following fire.

The residuals of paired-catchment regression models generally exhibit great heteroscedasticity and non-normality. However, the use of prediction intervals predicates that the regression model conforms to several statistical requirements. These requirements include the residuals being homoscedastic, independent, and normally distributed, along with the samples being evenly distributed in relation to the predicted values (Watson et al., 2001). Violation of these regression requirements can produce invalid prediction intervals (Sheather, 2009). Thus, application of prediction intervals for regression analysis necessitates the transformation of streamflow data to meet the statistical requirements.

A number of techniques have been established to transform non-linear data for use in linear regression. The most common method is to take the log of the test and control streamflow (Hirsch, 1982; Watson et al., 2001). This transformation has the effect of increasing the variance of low flows and decreasing the variance of high flows. While homoscedasticity and normality of streamflow residuals are often improved following a log–log transformation, Clarke (1994) has noted that streamflow data does not necessarily follow a log-normal distribution. Hence, the log–log transformation may not always be optimal for transforming streamflow data.

The Box–Cox power transformation is an adaptable transformation that is used to create a simple model out of transformed variables, as opposed to a more complex model out of original variables (Draper and Smith, 1981). The technique has seldom been applied in hydrology (Clarke, 1994; Kuczera, 1983). The Box–Cox transformation is defined as

$$y^{(\lambda)} = \begin{cases} (y^{\lambda} - 1)/\lambda & (\lambda \neq 0) \\ \log y & (\lambda = 0) \end{cases} \quad (2)$$

where $\lambda$ is the transformation parameter and $y$ is the original streamflow data value. Streamflow is raised to the power $\lambda$ for all $\lambda$-values except zero, when the Box–Cox transformation simplifies to a log transformation. The power $\lambda$ is determined by selecting a range of $\lambda$-values which are used as input into the maximum likelihood power value equation, which is computed as

$$L(\lambda) = -\frac{n}{2}\log(SSE/n) + (\lambda - 1)\sum_{i=1}^{n}\log(y_i) \quad (3)$$

where $L(\lambda)$ is the maximum likelihood power value, $n$ is the number of observations and $SSE$ is the sum of squared error (Ryan, 1997). The $\lambda$-value corresponding to the highest maximum likelihood power value is then selected for use in the Box–Cox transformation.

An example of the Box–Cox transformation process is presented in Fig. 1. The regression model in Fig. 1a uses untransformed streamflow data and displays typical heteroscedasticity and non-normality of the residuals, which contribute to an over and under-prediction of streamflow change when using predictions intervals at high and low flows, respectively. Streamflow in Fig. 1b has been transformed using the Box–Cox transformation with $\lambda$-values equal to 0.45 in the control catchments and 0.35 in the test catchment. The residuals from this regression model exhibit greater homoscedasticity and better approximate a normal distribution as compared to the original regression model. Fig. 1c shows the regression model with Box–Cox transformed data translated back into original streamflow units. The untransformed plot demonstrates that absolute uncertainty in the Box–Cox regression model increases with streamflow magnitude, mirroring the variance of the underlying streamflow data.

For this study, all paired-catchment regression models were developed using Box–Cox transformed data, differing from the Watson et al. (2001) approach. Statistically significant increases in post-fire streamflow were evaluated as those points that exceeded the upper prediction interval of the regression model. Post-fire values within the prediction interval were not considered to represent significant change. We recognize that there is some uncertainty in the transformation process related to the derivation of the optimal $\lambda$-values in the maximum likelihood power value equation, which may affect the placement of prediction intervals and the evaluation of post-fire streamflow change. However, we feel that this increase in uncertainty will have a smaller effect on the paired-catchment analysis than problems associated with an erroneous regression model.

Transformations of streamflow generally improve the fit of a regression model; however in some cases, the transformation may also produce influential points that can bias the regression model. Influential points can be identified using Cook's distance values, which measures the effect of removing each individual point on the regression model. Cook's distance is defined as

$$D_j = \frac{1}{ps^2}\sum_{i=1}^{n}(\hat{y}_{i(j)} - \hat{y}_i)^2 \tag{4}$$

where $p$ is the number of parameters, $s$ is the standard deviation, $n$ is the number of observations, and $\hat{y}_i$ and $\hat{y}_{i(j)}$ are the predicted values for observation $i$ from the full regression model and a modified regression model in which observation $j$ has been omitted, respectively (Ryan, 1997). In this study, points with Cook's distance values greater than one were considered to be influential (Ryan, 1997). Influential points were most commonly produced by transformations of very small streamflows (less than 1 mm) in which the streamflow in the two paired catchments differed by several orders of magnitude. The transformation process amplified this difference in streamflow, creating an outlier for the regression model. The impact of removing these influential points on the regression analysis was expected to be minimal since the values of the removed streamflow were close to zero.

## 4. Results and discussion

### 4.1. Paired catchments

#### 4.1.1. Catchment identification

Despite the large number of candidate catchments in this study, only six paired catchments were found to satisfy the selection cri-

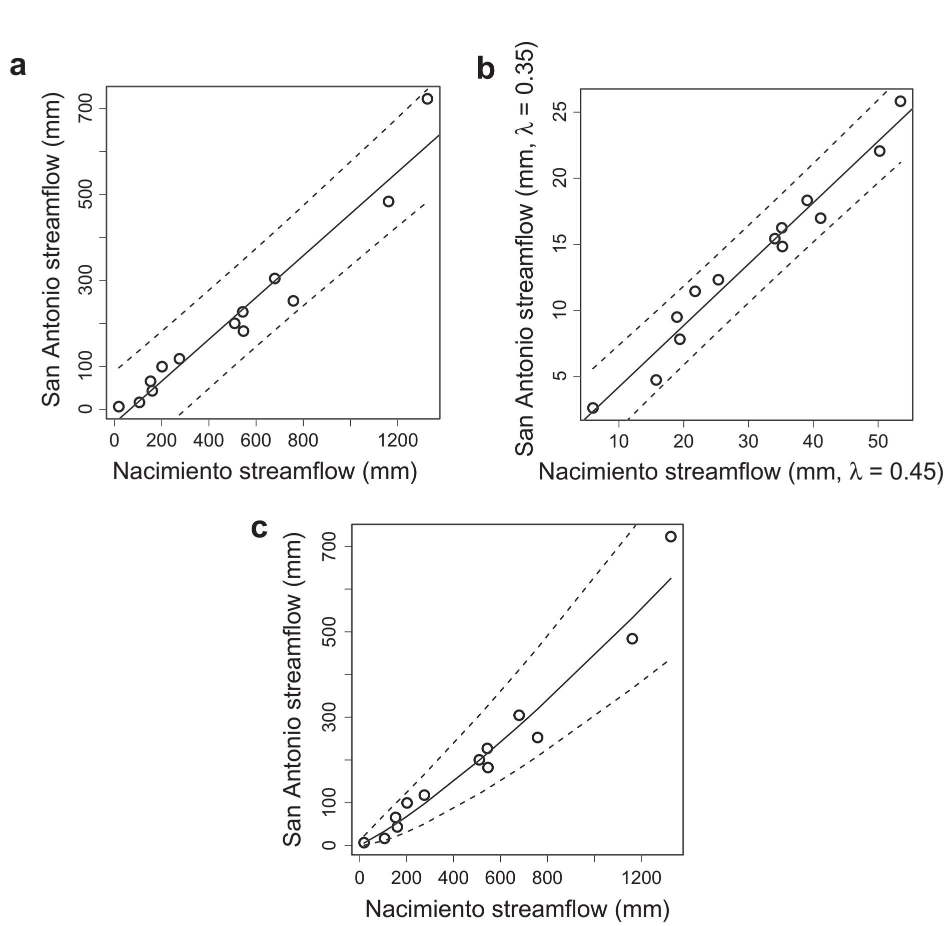


**Fig. 1.** Pre-fire regression model and prediction intervals (dashed lines) for test catchment San Antonio and control catchment Nacimiento for annual streamflow using: (a) original streamflow data, (b) Box–Cox transformed streamflow data and (c) Box–Cox transformed streamflow data translated back into original streamflow units.

teria outlined in Section 3.1. These included nine individual catchments, with one catchment, San Antonio, designated as both a test and a control catchment. Although catchment selection encompassed all of California south of latitude 39°N, all of the selected catchments were situated along a limited extent of the central California coast between Los Angeles and San Francisco (Fig. 2). Characteristics of the selected catchments are summarized in Table 1, while details regarding fire dates, area burnt, and distance between catchment pairs for each of the paired-catchment experiments is given in Table 2. All the catchments are underlain primarily with sedimentary rock, except for Nacimiento, where the lithology is granite/volcanic rock. Chaparral is the major vegetation in the burned areas of each of the catchments. Other common vegetation types include forests, oak woodlands and grasslands. All the catchments are undeveloped, with the exception of San Antonio, which contains a small amount of agriculture (less than 4% of total catchment area). Streamflow is measured in calibrated sections of the stream. Many of the streams are ephemeral with no streamflow during the summer dry season.

The primary challenge of catchment selection involved finding catchments with long records of stable land-cover conditions. Most catchments in central and southern California were subject to too many fires. The need to satisfy multiple criteria simultaneously; including a single fire in the test catchment, no fires in the control catchment, during the same period and within a certain proximity to one another; limited the availability of catchment pairs. Further, no catchment pair had more than 20 years available for model calibration, which may have had an effect on the strength of the calibration regression models. A number of compromises were necessary to find viable paired catchments from the existing network of streamflow gauges. The closest suitable control catchment for test catchments Sespe, Santa Paula, and Lopez was Santa Cruz, which was located over 41, 68 and 97 km from each of the respective test catchments (Fig. 2 and Table 2). For the Cantua catchment, the threshold of area burnt was lowered to 23% in order to increase the number of samples in the studies.

*4.1.2. Hydrological similarity*

With a few exceptions, the $R^2$ values for the calibration regression models were greater than 0.8 (Table 3), well above the 0.3 minimum threshold suggested by Loftis et al. (2001). The only relatively poor calibration relations were associated with the December time-period. This may have been a consequence of a timing mismatch in the resumption of streamflow at the beginning of the wet season due to differences in soil moisture storage capacity between the test and control catchment.

The strength of the calibration model appeared to be most affected by similarities in the rainfall-producing mechanisms of the test and control catchments (Tables 1 and 3). Rainfall patterns in these central California catchments are controlled primarily by orographic effects which can produce significantly different intensities and total rainfall amounts over short distances. Most of the study catchments fell into two broad rainfall categories defined by their orientation to the prevailing westerly winds, those on the dry leeward side of a principal orographic barrier and those on the wet windward side. The best regression relations occurred when the test and control catchment were in the same category. For example, the three catchments which had similar rainfall-producing mechanisms as their respective control catchments, namely, Arroyo Seco, San Antonio, and Santa Paula, also had the

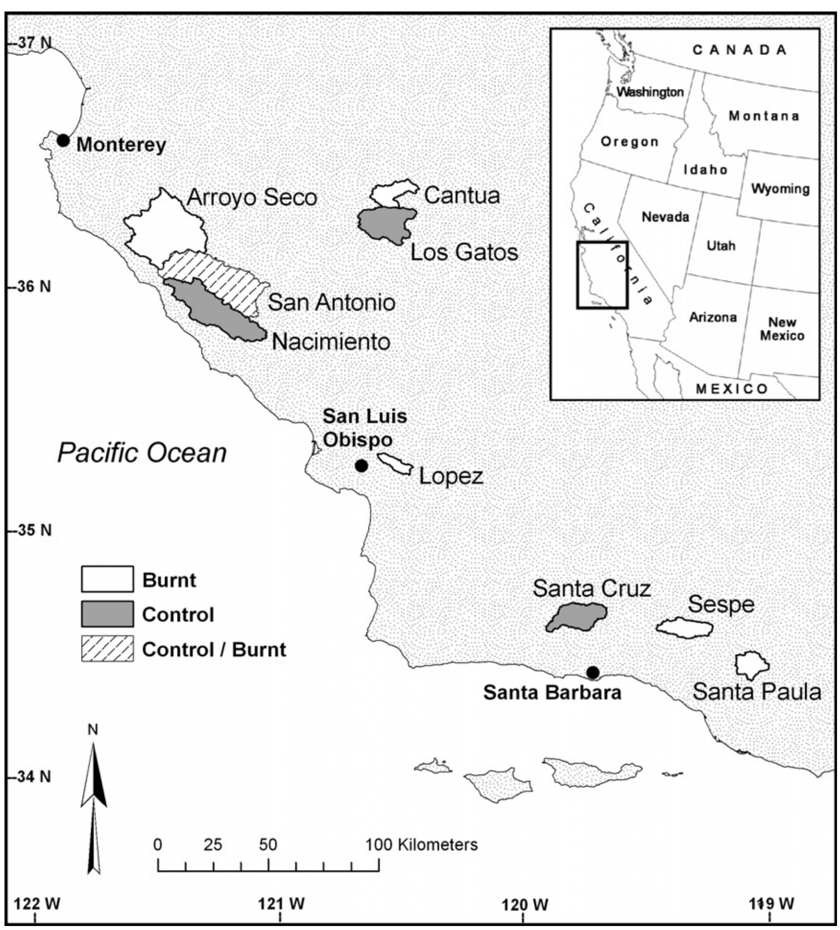


**Fig. 2.** Location of study catchments in California.

**Table 1**
Summary of catchment characteristics. Orographic type refers to the orientation of the catchment relative to the principle orographic barrier.

| Catchment name | USGS number | T/C | Area ($km^2$) | MAP (mm) | MAQ (mm) | Mean slope (%) | DD ($km/Km^2$) | Mean LAI | Orographic type |
|---|---|---|---|---|---|---|---|---|---|
| Arroyo Seco | 11152000 | T | 632 | 704 | 271 | 24.2 | 0.36 | 2.44 | Leeward |
| San Antonio | 11149900 | C | 562 | 580 | 181 | 15.6 | 0.40 | 1.83 | Leeward |
| Cantua | 11253310 | T | 119 | 442 | 26 | 18.1 | 0.32 | 1.28 | Variable |
| Los Gatos | 11224500 | C | 249 | 469 | 30 | 20.1 | 0.38 | 1.29 | Variable |
| Lopez | 11141280 | T | 54 | 689 | 179 | 27.2 | 0.36 | 3.25 | Leeward |
| Santa Cruz | 11124500 | C | 192 | 807 | 125 | 22.7 | 0.33 | 2.41 | Windward |
| San Antonio | 11149900 | T | 562 | 580 | 181 | 15.6 | 0.40 | 1.83 | Leeward |
| Nacimiento | 11149800 | C | 420 | 560 | 406 | 17.0 | 0.36 | 2.02 | Leeward |
| Santa Paula | 11113500 | T | 104 | 680 | 295 | 22.9 | 0.32 | 2.29 | Windward |
| Santa Cruz | 11124500 | C | 192 | 807 | 125 | 22.7 | 0.33 | 2.41 | Windward |
| Sespe | 11111500 | T | 130 | 707 | 163 | 19.6 | 0.35 | 1.80 | Leeward |
| Santa Cruz | 11124500 | C | 192 | 807 | 125 | 22.7 | 0.33 | 2.41 | Windward |

T: test catchment; C: control catchment; MAR: mean annual rainfall; MAQ: mean annual streamflow; DD: drainage density; LAI: leaf-area index.

**Table 2**
Details of the paired-catchment analysis.

| Test catchment | Fire year | Fire size (%) | Distance between Pairs (km) | Control period | Test period |
|---|---|---|---|---|---|
| Arroyo Seco | 1977 | 63 | 29 | 1966–1977 | 1978–1982 |
| Cantua | 1979 | 23 | 14 | 1967–1979 | 1980–1984 |
| Lopez | 1985 | 100 | 97 | 1968–1985 | 1986–1990 |
| San Antonio | 1985 | 31 | 14 | 1972–1985 | 1986–1990 |
| Santa Paula | 1985 | 71 | 68 | 1966–1985 | 1986–1990 |
| Sespe | 1985 | 40 | 41 | 1966–1985 | 1986–1990 |

**Table 3**
$R^2$ values for paired-catchment regressions models using Box–Cox transformed streamflow data.

| Test catchment | Annual | December | January | February | Winter | Spring |
|---|---|---|---|---|---|---|
| Arroyo Seco | 0.985 | 0.928 | 0.991 | 0.979 | 0.974 | 0.982 |
| Cantua | 0.894 | 0.371 | 0.982 | 0.936 | 0.938 | 0.941 |
| Lopez | 0.886 | 0.749 | 0.732 | 0.927 | 0.917 | 0.857 |
| San Antonio | 0.966 | 0.836 | 0.965 | 0.957 | 0.936 | 0.959 |
| Santa Paula | 0.933 | 0.880 | 0.844 | 0.933 | 0.936 | 0.951 |
| Sespe | 0.825 | 0.659 | 0.785 | 0.856 | 0.869 | 0.871 |

highest $R^2$ values (Tables 1 and 3). These $R^2$ values were all greater than 0.836 despite the Arroyo Seco and San Antonio pairs having the largest catchment areas in the study and Santa Paula being located 68 km away from its control catchment (Santa Cruz). In contrast, test catchments Lopez and Sespe were both located on the leeward side of their respective principle orographic barriers, while their control catchment Santa Cruz was windward. Consequently, the calibration models between these pairs had some of the lower $R^2$ values in the study, ranging from 0.659 to 0.927. The pairing of Cantua with its control Los Gatos was unique in that the primary orographic barrier in the catchment was located between the catchments, causing one catchment to be leeward while the other was windward, depending on the trajectory of the prevailing storms. The calibration model $R^2$ values for this pairing were above 0.894, apart from a very low value of 0.371 for the December time-period.

Proximity of paired catchments to one another was a secondary control on the strength of the paired-catchment regression model. While the highest $R^2$ values were generally associated with paired catchments that were close to one another, notable exceptions included the high $R^2$ values achieved between test catchment Santa Paula and its control Santa Cruz, despite the distance between these two catchments being the second farthest in the study (Table 2). The consistency in streamflow between distant catchments in this region was likely a product of the predominance of winter frontal systems, which tend to be spatially homogeneous over wide areas.

### 4.2. Post-fire streamflow analysis

A summary of post-fire streamflow observations which exceeded the respective upper prediction intervals in each test catchment is given in Table 4. The most notable finding was the lack of statistically significant post-fire streamflow change in these catchments. Only a few of the catchments showed any indication of change, and this change did not appear to be consistently associated with any of the time-periods, nor to fire size or catchment area. Further, no increase in streamflow was detected for Lopez after it burnt. Lopez was considered to have the highest likelihood for streamflow change since it was the smallest catchment (54 $km^2$) in the study and had the highest percentage of area burnt (100%). The regression plots for each of the paired-catchment experiments that exceeded the upper prediction interval of the pre-fire regression model are displayed in Fig. 3. The regression models were calibrated using transformed streamflow data and then translated back into original streamflow units to facilitate interpretation.

The primary control on streamflow response to land-cover change in this study appeared to be wetness conditions, with streamflow response exhibiting greater sensitivity during wet periods. This was investigated by examining streamflow changes in each test catchment relative to the corresponding annual rainfall time-series. The rainfall time-series were based on data provided by the Precipitation–Elevation Regressions on Independent Slopes Model (PRISM) project (http://www.prismclimate.org) (Fig. 4). Most changes in post-fire streamflow occurred during years when rainfall was near or greater than normal, with the exception of post-fire year four in Arroyo Seco (Table 4 and Fig. 4). In contrast, there was little indication of post-fire streamflow change during periods of below average rainfall. For instance, the four catchments which burned in 1985; Lopez, San Antonio, Santa Paula and Sespe; each experienced a prolonged drought during post-fire years two through five. These years coincided with no post-fire increases in streamflow (Table 4). Given the general correspondence between soil moisture conditions and rainfall, soil moisture was the likely determinant of streamflow response to land-cover change in this region. Since evaporative losses are largely under the control of soil moisture during dry periods; differences in vegetation cover and the transpirational capacity of test and control catchments likely had minimal effect on evaporative fluxes and hence streamflow.

**Table 4**
Summary of post-fire streamflow events that exceeded the upper pre-fire prediction interval. Numbers indicate the year following fire.

| Test catchment | Area ($km^2$) | Fire size (%) | Annual | December | January | February | Winter | Spring |
|---|---|---|---|---|---|---|---|---|
| Arroyo Seco | 632 | 63 | 5 | | 3, 4, 5 | | | 2, 4 |
| Cantua | 119 | 23 | | | 1 | | | |
| Lopez | 54 | 100 | | | | | | |
| San Antonio | 562 | 31 | 1 | | | | 1 | |
| Santa Paula | 104 | 71 | | | | | | |
| Sespe | 130 | 40 | | | 1 | | | |

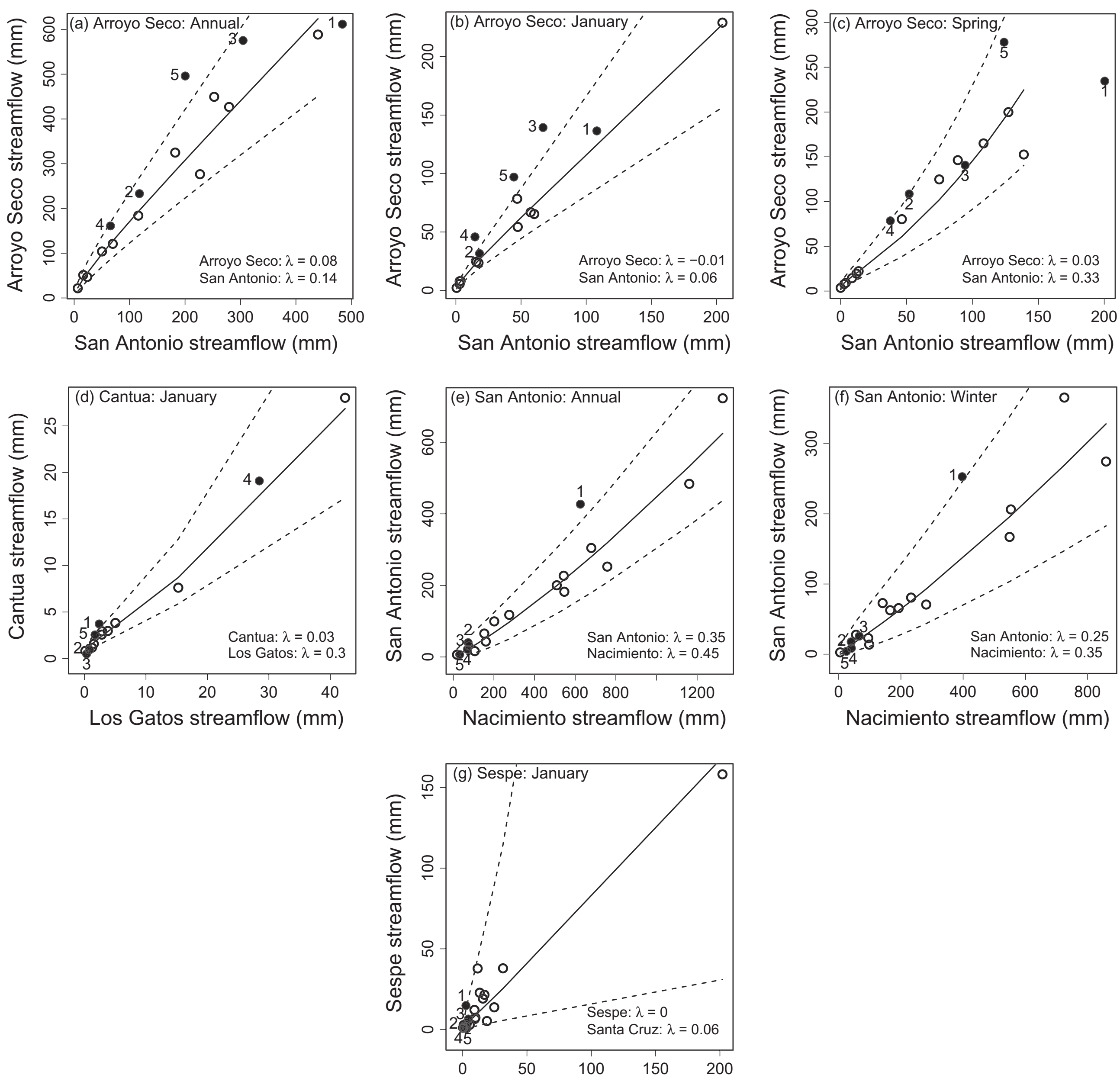


**Fig. 3.** Catchments and associated time-periods where post-fire streamflow exceeded the upper prediction interval of the pre-fire regression models. The regression models were calibrated using transformed streamflow with the $\lambda$-values shown and then translated back into original streamflow units. Open circles represent pre-fire streamflow, solid circles represent post-fire streamflow and numbers indicate the year following fire. Dashed lines represent prediction intervals. The control catchment is on the $x$-axis.

During wet periods, control over evaporation shifts from soil moisture to the transpirational capacity of vegetation. It is during these periods that differences in vegetation following fire may have impacted streamflow. Nonetheless, post-fire streamflow change was not ubiquitous during wet years, indicating that other factors may have affected post-fire streamflow response or that the calibration models lacked the precision to reveal significant changes in streamflow.

The ability to detect statistically significant streamflow change in these catchments was affected by the strength of the calibrated

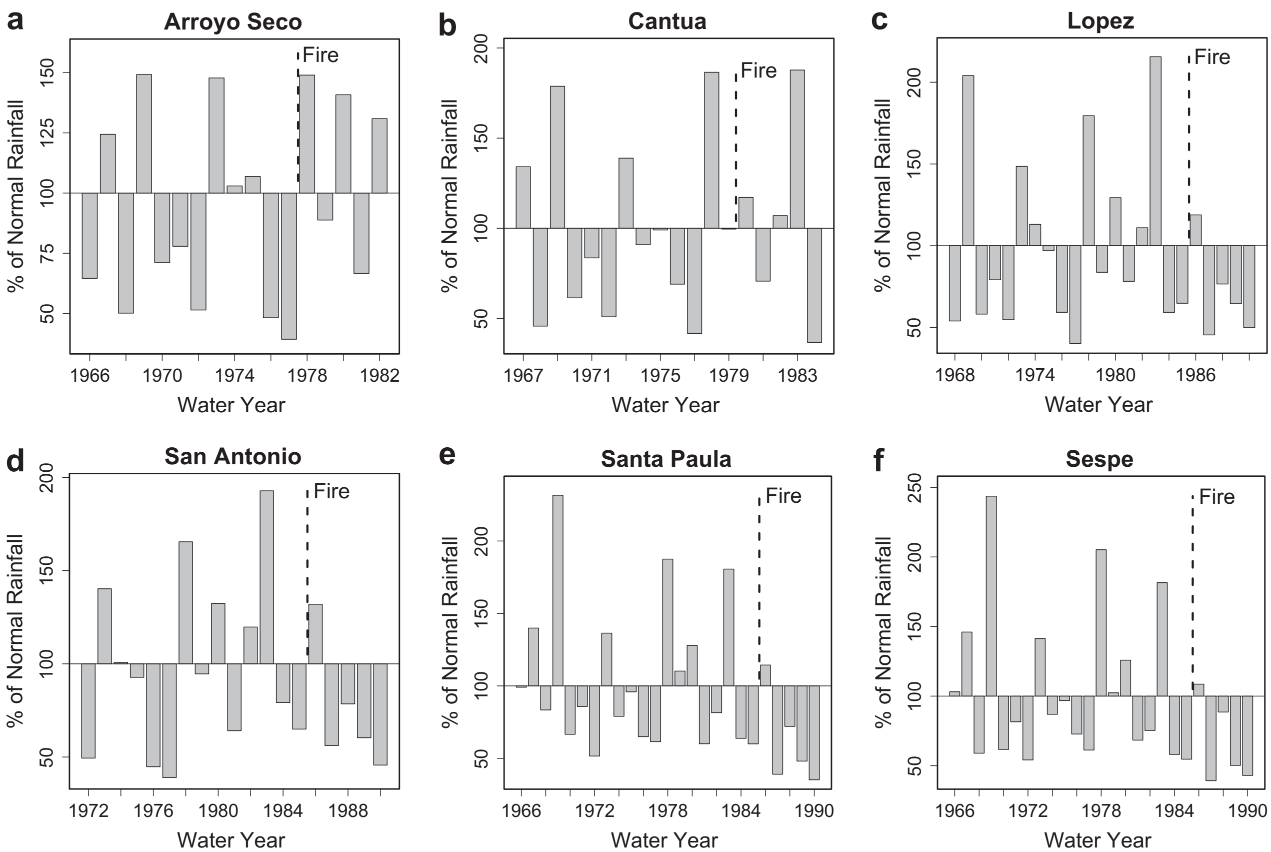


**Fig. 4.** Annual rainfall time-series for test catchments.

paired-catchment regression models. For example, the small Lopez catchment with 100% area burnt showed no indication of post-fire streamflow change. Yet Arroyo Seco and San Antonio, the two largest catchments of the study with burnt areas of 63% and 31%, respectively, did exhibit some change. These outcomes may not reflect true differences in streamflow response to fire, but may possibly be attributed to Arroyo Seco and San Antonio having some of the highest $R^2$ values in the study, with Lopez having some of the lowest (Table 3). Minimizing uncertainty in pre-fire calibration models may be crucial for detecting potentially small changes in post-fire streamflow in large MCR catchments.

Monthly and seasonal streamflow volumes appeared to be insensitive to potential increases in hydrophobicity caused by fires. There were only a few instances of streamflow change exceeding model uncertainty during these time-periods (Table 4). Although post-fire streamflow peaks may have increased during the wet winter period, the volume of streamflow increase over each month or season was likely a small proportion of the total monthly and seasonal flows. In addition, the impact of hydrophobicity on the streamflow may have been minimized by heterogeneity in catchment characteristics and variations in fire behavior, which may have caused hydrophobic soil production to not be ubiquitous across a catchment (Shakesby and Doerr, 2006).

The spring period showed a similar lack of significant post-fire streamflow change, despite greater likelihood of differences in transpirational capacity between the test and control catchments during this period (Table 4). Two important processes may have accounted for this outcome and maintained transpiration levels at pre-fire levels in the burnt catchments. First, field studies (e.g. Keeley and Keeley, 1981) and satellite-based studies (e.g. Hope et al., 2007) have shown that chaparral post-fire recovery is very rapid, with the greatest recovery occurring in the first five years following a fire. Furthermore, most of the recovery in transpirational capacity takes place in the first post-fire year since pyric succession is characterized by herbaceous and annual species dominating the landscape immediately following the fire, along with a rapid re-growth of resprouting shrubs. Second, it is unknown to what degree and intensity the catchment landscape, and the riparian zone in particular, burned in these fires. Riparian vegetation is often composed of deciduous trees and shrubs that have contrasting characteristics to chaparral in terms of transpiring leaf area and access to the saturated zone (Dwire and Kauffman, 2003). If riparian vegetation remained intact following the fire, then its ability to transpire at potential rates could have maintained a significant proportion of the catchment-scale transpirational losses.

## 5. Conclusions

The primary objective of this study was to evaluate the effects of fire on streamflow volumes in large catchments of central and southern California using a paired-catchment approach. Given that the study focused on large, non-experimental catchments, it was necessary to introduce a novel paired-catchment methodology that attempted to exploit streamflow data from a routine gauging network to deduce the effects of fires on streamflow volumes.

The effect of fires on streamflow, regardless of time-period examined, was found to be variable, depending mostly on post-fire wetness conditions. Despite large areas of the catchments being burnt, little statistically significant post-fire streamflow change was evident during dry periods, when soil moisture was likely a primary control over transpiration. Under wet conditions, when transpirational control shifted from soil to vegetation, there was greater, but not consistent, evidence of streamflow change. This variability in hydrologic response to fire is consistent with the mixed results reported in the literature regarding the effects of land-cover change on streamflow in large catchments. No relation was discerned between post-fire streamflow change and catchment size or area burnt.

There was no noticeable increase in streamflow in any of the catchments during the spring period, when differences in transpiration between burnt and unburnt catchments were expected to be greatest. There was also no evidence of hydrophobicity affecting post-fire streamflow in the wet season months immediately following the fires. This finding may have been a consequence of analyzing monthly time-periods as opposed to an analysis of event-based peak flows. While hydrophobicity may cause a clear increase in storm-event peaks, the overall change to the monthly streamflow volume (stormflow plus baseflow) may be small and difficult to detect against the uncertainty inherent in the streamflow data and paired-catchment calibration equations.

The use of non-experimental catchments in paired-catchment studies appeared to be a viable empirical approach for quantifying streamflow response to land-cover change in large catchments. However, this study demonstrated that the approach may be limited by the challenge of finding paired test and control catchments. Despite the large number of available network stream gauges, most potential catchments in this region were subject to frequent fires so that long periods with stable land-cover conditions were difficult to identify. Still, the potential relaxation of paired-catchment assumptions associated with rainfall and hydrological similarity had surprisingly little effect on the pre-fire calibration models. High $R^2$ values (generally greater than 0.8) were obtained for calibration models using monthly, seasonal and annual streamflow volumes. The best calibration results were associated with catchment pairs that had similar orographic controls over rainfall production, with proximity to one another being a secondary control.

The spatial and temporal characteristics of rainfall in the central and southern California region appeared to have a considerable effect on the implementation of the paired-catchment approach, as well as the interpretation of the streamflow change results. Consequently, the application of this methodology in other studies is likely best suited to regions where the spatial patterns of rainfall are broadly uniform and vegetation, as opposed to soil moisture, is the primary control on transpiration. Further, as one of the primary challenges of the methodology was the identification of appropriate paired catchments, the technique may be more successful in regions that are subject to less frequent episodic changes in land cover.

## Acknowledgements

This study was funded by the US National Aeronautics and Space Administration, Land Cover Land Use Change Program, Grant No. NNG05GR14G. We are very grateful for the assistance of Dillon Fitch, Dan Hawtree, and Noah Albers, as well as the comments provided by two reviewers.

## References


Andréassian, V., 2004. Waters and forests: from historical controversy to scientific debate. Journal of Hydrology 291, 1–27.

Andréassian, V., Parent, E., Michel, C., 2003. A distribution-free test to detect gradual changes in watershed behavior. Water Resources Research 39, 1252.

Aronica, G., Candela, A., Santoro, M., 2002. Changes in the hydrological response of two Sicilian basins affected by fire. In: van Lanen, H.A.J., Demuth, S. (Eds.), FRIEND 2002 – Regional Hydrology: Bridging the Gap Between Research and Practice. IAHS Publ. 274. IAHS Press, Wallingford, UK, pp. 163–169.

Best, A., Zhang, L., McMahon, T., Western, A., Vertessy, R., 2003. A Critical Review of Paired Catchment Studies with Reference to Seasonal Flows and Climatic Variability, CSIRO Land and Water Technical Report 25/03. Murray-Darling Basin Commission, Canberra, Australia.

Bosch, J.M., Schulze, R.E., Kruger, F.J., 1984. The effect of fire on water yield. In: Booysen, P.D., Tainton, N.M. (Eds.), Ecological Studies 48: Ecological Effects of Fire in South African Ecosystems. Springer-Verlag, New York, USA, pp. 327–348.

Bracken, L.J., Croke, J., 2007. The concept of hydrological connectivity and its contribution to understanding runoff-dominated geomorphic systems. Hydrological Processes 21, 1749–1763.

Britton, D.L., 1991. Fire and the chemistry of a South African mountain stream. Hydrobiologia 218, 177–192.

Clarke, R.T., 1994. Statistical Modeling in Hydrology. John Wiley and Sons, Chichester, UK.

DeBano, L.F., Neary, D.G., Ffolliott, P.F., 1998. Fire's Effects on Ecosystems. John Wiley and Sons, New York, USA.

Draper, N.R., Smith, H., 1981. Applied Regression Analysis. John Wiley and Sons, New York, USA.

Dwire, K.A., Kauffman, J.B., 2003. Fire and riparian ecosystems in landscapes of the western USA. Forest Ecology and Management 178, 61–74.

Haan, C.T., 2002. Statistical Methods in Hydrology, 2nd ed. Iowa State Press, Ames, Iowa.

Hessling, M., 1999. Hydrological modelling and a pair basin study of Mediterranean catchments. Physics and Chemistry of the Earth, Part B: Hydrology, Oceans and Atmosphere 24, 59–63.

Hirsch, R.M., 1982. A comparison of four streamflow record extension techniques. Water Resources Research 18, 1081–1088.

Hocking, R.R., 2003. Methods and Applications of Linear Models: Regression and the Analysis of Variance, 2nd ed. John Wiley and Sons, Hoboken, New Jersey.

Hope, A., Tague, C., Clark, R., 2007. Characterizing post-fire vegetation recovery of California chaparral using TM/ETM+ time-series data. International Journal of Remote Sensing 28, 1339–1354.

Hoyt, W.G., Troxell, H.C., 1934. Forests and stream flow. Paper No. 1858, vol. 99. American Society of Civil Engineers, Transactions, pp. 1-111.

Jung, H.Y., Hogue, T.S., Rademacher, L.K., Meixner, T., 2009. Impact of wildfire on source water contributions in Devil Creek, CA: evidence from end-member mixing analysis. Hydrological Processes 23, 183–200.

Keeley, J.E., Keeley, S.C., 1981. Post-fire regeneration of southern California chaparral. American Journal of Botany 68, 524–530.

Kuczera, G., 1983. Improved parameter inference in catchment models 1. Evaluating parameter uncertainty. Water Resources Research 19, 1151–1162.

Lavabre, J., Torres, S., Cernesson, F., 1993. Changes in the hydrological response of a small Mediterranean basin a year after a wildfire. Journal of Hydrology 142, 273–299.

Lenihan, J.M., Drapek, R., Bachelet, D., Neilson, R.P., 2003. Climate change effects on vegetation distribution, carbon, and fire in California. Ecological Applications 13, 1667–1681.

Lindley, A.J., Bosch, J., van Wyk, D.B., 1988. Changes in water yield after fire in fynbos catchments. Water SA 14, 7–12.

Liu, S., Leslie, L.M., Speer, M., Bunker, R., Mo, X., 2004. The effects of bushfires on hydrological processes using a paired-catchment analysis. Meteorology and Atmospheric Physics 86, 31–44.

Loáiciga, H.A., Pedreros, D., Rob erts, D., 2001. Wildfire-streamflow interactions in a chaparral watershed. Advances in Environmental Research 5, 295–305.

Loftis, J.C., MacDonald, L.H., Streett, S., Iyer, H.K., Bunte, K., 2001. Detecting cumulative watershed effects: the statistical power of pairing. Journal of Hydrology 251, 49–64.

McMichael, C.E., Hope, A.S., 2007. Predicting streamflow response to fire-induced landcover change: Implications of parameter uncertainty in the MIKE SHE model. Journal of Environmental Management 84, 245–256.

Moreno, J.M., Oechel, W.C., 1995. Global Change and Mediterranean-type Ecosystems. Springer-Verlag, New York, USA.

Neary, D.G., Ffolliott, P.F., 2005. The water resource: Its importance, characteristics, and general response to fire. In: Neary, D.G., Ryan, K.C., DeBano, L.F. (Eds.), Wildland Fire in Ecosystems: Effects of Fire on Soil and Water. General Technical Report RMRS-GTR-42, Ogden UT, USDA Forest Service, Rocky Mountain Research Station, pp. 95–106.

Ryan, T.P., 1997. Modern Regression Methods. John Wiley & Sons Inc., New York, USA.

Scott, D.F., 1993. The hydrological effects of fire in South African mountain catchments. Journal of Hydrology 150, 409–432.

Scott, D.F., Van Wyk, D.B., 1990. The effects of wildfire on soil wettability and hydrological behaviour of an afforested catchment. Journal of hydrology 121, 239–256.

Service, R.F., 2004. As the west goes dry. Science 303, 1124–1127.

Shakesby, R.A., Doerr, S.H., 2006. Wildfire as a hydrological and geomorphological agent. Earth Science Reviews 74, 269–307.

Sheather, S.J., 2009. A Modern Approach to Regression with R. Springer.

Watson, F., Vertessy, R., McMahon, T., Rhodes, B., Watson, I., 2001. Improved methods to assess water yield changes from paired-catchment studies: application to the Maroondah catchments. Forest Ecology and Management 143, 189–204.

Williams, A.A.J., Karoly, D.J., Tapper, N., 2001. The sensitivity of Australian fire danger to climate change. Climatic Change 49, 171–191.