An Analysis of the 9 January 2018 Montecito, California Post-fire Runoff Event Using GSSHA Hydrological Model

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Abstract

Inundation models that realistically simulate hydrologic processes are in demand for post-wildfire flood susceptible regions like Southern California where precipitation occurrences, increasing population densities, fire-prone vegetation, and steep terrain combined with wildfires, trigger flooding events. In Santa Barbara and Ventura Counties following the 2017 Thomas Fire, on January 9th, 2018, an intense atmospheric river flood resulted in a series of destructive water and debris flows causing major damage to life and property. This study utilizes the physics-based Gridded Surface Subsurface Hydrological Analysis, GSSHA, a watershed numerical model to simulate the flood events in the San Ysidro Creek watershed. To assist in reducing uncertainties affecting model predictions, a parametric sensitivity analysis of the post-fire runoff process was applied using the "Shuffled Complex Evolution", SCE optimization algorithm. To reduce uncertainty, two methods of parameterization were applied: parameter transfer and optimization. It was found feasible to establish a transfer of parameters from a nearby, comparable watershed based on a previous study conducted by Pradhan and Floyd (2021). The key parameters that were identified in the sensitivity analysis were manning's roughness and the hydraulic conductivity reduction factor. Although sensitive to both parameters, the model was found to be significantly more sensitive to the change in hydraulic conductivity reduction factor. Both types of parameterization found that post-fire simulations compared well to the observed data for the 09 January 2018 rainfall event. The post-wildfire numerical modeling approach provided an improvement to the existing state-of-practice for predicting post-wildfire inundation risks. Understanding post-fire hydrologic processes and improvements in modeling is crucial in providing a framework for emergency assessments and therefore potentially reduce the impacts of post fire flooding on landscapes, infrastructure (e.g., roads, reservoirs), and communities.

Introduction

Background

In recent decades, wildfires have increased in severity and frequency making it a major concern in the western US and other parts around the world. Post-wildfire storm events frequently create large runoff volumes, sometimes in the form of debris flows (water-laden slurries of soil and rock that move rapidly through channels in steep landscapes), that cause damage to life, property, infrastructure (e.g. reservoir), and environment (air, land, water) (Cannon et al., 2008; Barnhart and Jones, 2021; Floyd, 2021). Predictions of post-wildfire flooding and debris flows are crucial to be prepared for emergency response after a wildfire. Currently, there is a demand for a physics-based hydrological framework that requires accurate parameterization of soil-hydraulic properties to reduce model uncertainty (Lane et al., 2006; Cannon and DeGraff, 2009; Moody, 2013). Southern California is a region in the US that can particularly benefit from improvements in post-wildfire model parametrization due to the frequency of wildfires in the area (Ebel and Moody, 2020). Wildfire in chaparral-vegetated basins affects hydrology, soil properties, and slope stability and causes an increase in the rate of sediment production and yield from hillslopes and in sediment yield from rivers (Florsheim et al., 1991; Scott and Williams, 1978; Rice, 1974). Uncertainty in future climate change, the existence of fire-prone vegetation along steep terrain and increasing human activity in the area all contribute to Southern California's predominantly high risks for post-wildfire floods and debris flows.

For example, the 2017 Thomas Fire, one of the largest fires in modern California history, demonstrated this need for readily available hazard assessment tools, after it burned 440 square miles through Santa Barbara and Ventura Counties. Following the fire, on January 9th, 2018, an intense atmospheric rainfall event occurred with an intensity of 0.2% to 0.5% annual percent chance exceedance, triggering a series of destructive debris flows that mobilized 680,000 m^3 of sediment in the Santa Ynes Mountains. This resulted in 23 fatalities, 167 injuries, 408 damaged homes, and $1.3 Billion in damages (Kean et al, 2019). Before the debris-flow event, the best available predictions on potential inundation came from county, state, and federal floodplain maps (e.g., US Federal Emergency Management Agency [FEMA] 100-year floodplain). While valued, the floodplain maps do not account for fundamental differences in flow dynamics between water flows and debris flows (Kean et al, 2019). Hence, numerical modeling is a tool that can be used to predict post-wildfire inundation and debris flows. A numerical model that may support post-fire parametrization demands is U.S. Army Corps of Engineers (USACE) GSSHA, Gridded Surface Subsurface Hydrological Analysis, as it was designed to correctly identify and realistically simulate these two important hydrologic processes in watersheds (Downer and Ogden, 2006; Pradhan and Floyd, 2021). In this study, GSSHA was implemented to inform the potential for mitigation of the effects from inundation and debris-flow disasters in the future.

Several models and techniques have been available to predict post-fire runoff, varying from complexity and usability, and different modeling approaches may be suitable based on the watershed size. According to a survey on Burned Area Emergency Response (BAER) models, the five most common post-fire hydrologic models are empirical, semi-empirical, and semi-distributed: 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) (Kinoshita et al., 2014). Hydrologic models are fundamental tools in the decision-making process for emergency response, yet, they were not designed for post-fire conditions, so they need to be adjusted accordingly (Zema, 2021). A better understanding of precipitation, infiltration, erosion, and runoff will lead to improved predictive modelling capabilities. The existing hydrological models should be specifically adapted to burned conditions with a reliable simulation of soil changes due to fire. Past models have limited their evaluations to existing models underburned and unburned conditions (Lopes et al., 2021). Therefore, there is a necessity for the development of fire-affected soil hydraulic functions and special conditions related to wildfires (Moody, 2013).

Parameters are part of a numerical model structure that are used to characterize the environment that is being simulated. For example, in a watershed model, it is important to have different parameters such as soil type, initial moisture content, and infiltration rates for accurately simulating surface runoff. By setting these parameters as closely as possible to what exists in the prototype, the model results are more likely to resemble events that occur in the real world. Poor identification of some of the parameters as well as errors in the model structure are the main contributors to the model uncertainty. Several watersheds around the world are either ungauged or poorly ungauged, therefore many regionalized studies provide a relationship between parameters of the model and the catchment descriptors so that parameters are transferable to similar regions (Pradhan et al., 2008). A proper and detailed analysis of the parameters of a model and the model structure thereof can help estimate and reduce the uncertainties that can affect model predictions. To this end, a sensitivity analysis and estimation of predictive uncertainty have become central research topics in the hydrological modeling community (Abebe et al., 2010). The work by Spear and Hornberger (1980), the Generalized Likelihood Uncertainty Estimator (GLUE) approach of Beven and Binley (1992) and the Shuffled Complex Evolution (SCE) method of Duan et al. (1992) are among others for automatic calibration using optimization algorithms.

The purpose of this study was to implement GSSHA to model pre- and post-fire conditions that allowed to locate dominant processes in relation to the model structure development for post-wildfire hydrologic modeling. A sensitivity analysis was performed using the SCE optimization algorithm.

Objectives and Approach:

The objectives of this research are to a) utilize GSSHA to model pre- and post-fire conditions, b) identify the most dominant parameters in relation to the model structure including relevant physical processes (i.e. change in surface roughness, infiltration, etc.) in post-wildfire hydrologic modelling, c) perform a sensitivity analysis and analyze and assess if optimized parameters and parameter dominance can be generalized. To reduce uncertainty, two methods of parameterization were applied: parameter transfer and optimization. First, a transfer of parameters of a nearby watershed with similar physical properties were used to simulate pre- and post- fire scenarios for the Santa Barbara watershed. Then, the SCE optimization algorithm was applied to calibrate a hydrologic parameter. By applying both methods of parameterization, generalization of the optimized parameter values were assessed by the validity of those parameter conditions in nearby watersheds under similar conditions.

Methodology

Intense wildfires reduce vegetation canopy and catalyze several changes to soil properties that vary spatially and alter the soil profile (Moody, 2013). Infiltration rates are a function of various factors where hydraulic conductivity plays a critical role (Ebrahimian et al., 2019). Water distribution and flow in the vadose zone, are strongly influenced by the intrinsic properties of the soil matrix (John and Fuentes, 2021). Chemical and physical changes to the soil structure affect infiltration and hydraulic conductivity, and a reduction in vegetation affects surface roughness. Accordingly, a sensitivity analysis of hydraulic conductivity and surface roughness using GSSHA were analyzed using the SCE optimization algorithm and the identification of the model parameters were analyzed in relation to model structure development for post-wildfire hydrology.

GSSHA represents a fully coupled surface water/groundwater simulator with sediment transport capability. The model can simulate different types of runoff generation mechanisms including the infiltration excess mechanism defined by Richards' equation and the Green and Ampt method (1911). Numerous free surface flows are unsteady and non-uniform where spatial and temporal changes of water stages and flow discharges need to be determined (Leon, 2013). Channel routing in GSSHA uses an explicit solution of the diffusive wave equation (Julien and Saghafian 1995). Recent developments in GSSHA also include post-wildfire runoff generation mechanisms. In addition, the model has a robust transport mechanism that includes runoff routing coupled with soil erosion, transport, and deposition. This study included runoff generation and routing mechanisms in the model development process as well as the model's structural and parametric analysis process.

At times, numerical models contain parameters that cannot be measured directly but only be inferred by a calibration process that adjusts values to match the model to the real system it represents (Abebe et al., 2010; Madsen, 2000). Traditional calibration procedures are labor intensive and involve frequent manual adjustments. Therefore, automatic methods for model calibration have become a common practice. A powerful, efficient procedure is the Shuffled Complex Evolution (SCE) method, a global optimization algorithm, initially developed by Duan et al. (1992). Various case studies have demonstrated that the SCE algorithm is consistent and efficient in locating optimal model parameters of a hydrological model (Vrugt and Bouten, 2003). SCE is based on four concepts: (1) combination of probabilistic and deterministic approaches; (2) clustering- shuffling of complexes and information sharing; (3) systematic evolution of a complex of points spanning the space, in the direction of global improvement; and (4) competitive complex evolution (Duan et al., 1992).

Hydrologic Processes

Understanding hydrologic processes of a watershed is not possible with only rainfall (input) and discharge (output) data as many processes may lead to comparable hydrographs. Rainfall and discharge, alone, do not provide adequate information of hydrologic response. Therefore, the identification of runoff generation and routing processes requires further investigation within the catchment basin to accurately characterize dominant water flow pathways (Latron and Gallart, 2008). In this study, runoff generation and routing processes are examined.

Runoff Generation:

Runoff occurs due to excess precipitation that flows until it reaches streams, rivers, and oceans and varies within time and space. Critical controls for runoff generation are precipitation intensity, duration of precipitation, and infiltration/storage capacity of the soil (Tindall and Kunkel, 1999). Following a high intensity wildfire, runoff can significantly increase through a loss of vegetation precipitation interception canopy (Floyd, 2021). Wildfires change infiltration soil properties, sometimes making the soil hydrophobic (water-repellent). Therefore, it is critical to observe infiltration and how it relates to changes in burn conditions.

Infiltration:

Infiltration is the process whereby rainfall and ponded surface water seep into the soil due to gravity and capillary suction. Green and Ampt (1911) developed a simple infiltration model that is theoretically based on Darcy's Law with physically significant parameters that can be computed from soil properties. Water is assumed to enter the soil as a sharp wetting front. Precipitation on initially dry soil quickly infiltrates due to capillary pressure and as rainfall continues, the ground becomes saturated and the infiltration rate will decrease until it approaches the saturated hydraulic conductivity of the soil. Infiltration rate is a function of hydraulic conductivity, pressure head, total porosity, effective porosity and saturation, and cumulative infiltration depth and is expressed as:

$$f(t) = K\left[\frac{h_p \Delta p_0}{F(t)} + 1\right] \tag{1}$$

Where: f(t) = infiltration rate at time t

K = hydraulic conductivity

H_p = pressure head for wetting at the wetting front

P_o = total porosity

P_{oi} = initial water content

P_{or} = residual water content

P_{oe} = po - por = effective porosity

S_e = poi/poe = Effective saturation

$\triangle p_o = p_o - p_{oi} = p_{oe} - S_e p_{oe} = (1 - S_e)p_{oe}$ = change in total porosity

F(t) = cumulative infiltration depth at time t

Post-fire Condition:

Accounting for changes in infiltration with changing burn severities is valuable for accurately predicting hydrological response. Pradhan and Floyd (2021) developed a post-fire condition formulation that includes multiplying factors, based on the physics based Green & Ampt distributed vadose zone infiltration process, which are explicitly linked to burned severities, to reduce an unburned soil hydraulic conductivity. Accordingly, the multiplying factors incorporate soil hydraulic conductivity reduction factor, and burned severity factor as follows:

$$k_{burned} = RF_k \cdot BDF \cdot k_{unburned} \tag{2}$$

Where: k_{burned} = soil hydraulic conductivity at burned condition

RF_k = Reduction Factor of soil hydraulic conductivity under burned condition

BDF = Burn Degree Factor

$k_{unburned}$ = soil hydraulic conductivity at normal unburned condition

In calibration, the reduction factor (RF_k) was considered from 0.05 to 0.90 (95% to 10% reduction range).

Routing:

Routing is essential in estimating the propagation of flood from upstream to the downstream of a river, lakes, and reservoirs. Understanding routing processes can help predict the hydrograph shape following rainfall events in a watershed. Hydraulic or distributed routing is based on the solution of partial differential equations of unsteady open-channel flow, and the equations used are the Saint-Venant equations. The hydraulic models require gathering a lot of data to solve the equations numerically. GSSHA uses the diffusive wave equation to model 1-D channel and 2-D overland flow routing and requires surface roughness to be applied at every cell grid to relate to flow rate.

Diffusive Wave:

Channel routing in GSSHA is simulated using an explicit solution of the diffusive wave approximation from the Saint-Venant Equations which combines the continuity and momentum equations. Since it is a non-linear equation, it requires numerical methods and large quantities of measured data. The diffusive wave is valid when the inertial acceleration is less than gravity, friction, and pressure terms, primarily where there is subcritical flows, with low Froude values:

Continuity

Conservation form $$\frac{\partial Q}{\partial x} + \frac{\partial A}{\partial x} = 0 \qquad (3)$$

Momentum

Conservation form $$\frac{1}{A}\frac{\partial Q}{\partial t} + \frac{1}{A}\frac{\partial}{\partial x}\left(\frac{Q^2}{A}\right) + \frac{\partial y}{\partial x} - g\left(S_0 - S_f\right) = 0 \qquad (4)$$

The diffusive wave model (also known as the non-inertia model) is written as:

$$g\frac{\partial y}{\partial x} - g\left(S_0 - S_f\right) = 0 \qquad (5)$$

Where: x = longitudinal distance along the channel or river

y = depth of flow

g = acceleration due to gravity

S_o = channel bottom slope

S_f = friction slope

Surface Roughness:

Water on the soil surface that neither infiltrates nor evaporates will pond on the surface, it can also move from one grid cell to the next as overland flow. Overland flow in GSSHA employs the same methods described for 1-D channel routing, except with calculations made in two dimensions. Numerical models such as GSSHA implement Manning's equation to relate surface roughness to flow rate:

$$Q = \frac{1}{n} A R^{\frac{2}{3}} S_f^{\frac{1}{2}} \tag{6}$$

Where: A = channel flow cross sectional Area

P = wetted perimeter

R = $\frac{A}{P}$ = hydraulic radius

S_f = friction slope

n = Manning's roughness coefficient

Surface roughness is an important parameter as it controls runoff on hillslopes and in channels through the frictional resistance parameter (Moody et al., 2013).

Parameterization:

Providing adequate information of the physical processes of a system to model and defining parameter values for a hydrologic model application (i.e., parameterization) are crucial and difficult tasks. Generally model applications use a combination of measured, estimated, and optimized parameter values (Malone et al., 2015). Parameterization is critical in order to avoid methodological problems at the subsequent phases of model calibration and validation. According to Refsgaard and Storm (1996), parameter values should be defined from as much available field data as possible, for the parameters subject to calibration physically acceptable ranges should be estimated, and the number of calibrated parameters should be kept low.

In lumped conceptual models, parameters do not have a physical meaning, therefore parametrization is not restricted to physical boundaries. By definition, a distributed physically based model, such as GSSHA, contains parameters that can be assessed from field measurements (Feyen et al, 2000). Due to the Thomas wildfire following intense rainfall, parameters were not directly assessed and therefore require particular calibration and validation. Fortunately, a similar study was assessed in a nearby watershed in southern California (Pradhan and Floyd, 2021), therefore parameters can be transferred accordingly. For redundancy, the two methods of parameterization in this study are parameter transfer and optimization.

Parameter Transfer:

The Santa Barbara watershed were modeled after the Arroyo Seco watershed due to its proximity and similarities (Pradhan and Floyd, 2021). Geographic coordinates of the watersheds are shown in Table 1. The watershed is located in Southern California, 82 miles away from the Santa Barbara watershed (Figure 1) and is part of the Transverse Range. Both studies (Arroyo Seco and San Ysidro Creek) were based on event-based simulations.

Table 1. Geographic coordinates for each watershed.

Watershed	Latitude	Longitude
San Ysidro Creek	34°29'08" North	119°36'03" West
Arroyo Seco	34°13'20" North	118°10'36" West

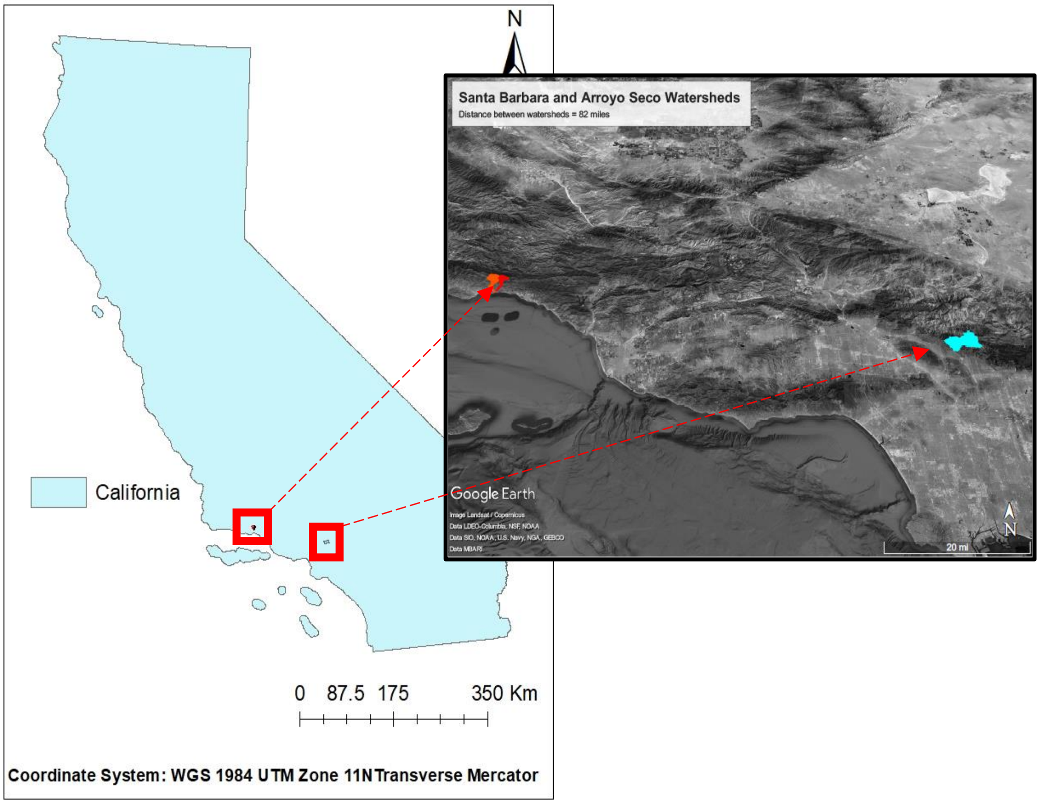

Figure 1. Distance between San Ysidro and Arroyo Seco watersheds located in Southern California.

The Arroyo Seco watershed was calibrated using the 2008 National Land Cover Database (NLCD) prior to the fire (Figure 2). According to the 2008 NLCD, San Ysidro Creek had a similar land use type for the burned portion of the watershed (Figure 3). The San Ysidro Creek southern portion was not burned and mostly residential, developed land. Otherwise, the majority of the area was 19.81% shrub/scrub, 30.98% mixed forest, and 28.14% evergreen forest. Arroyo Seco had a majority land use type of 56.52% shrub/scrub, 35.50% evergreen forest, and 4.99% mixed forest. The Arroyo Seco watershed is closer north of the Transverse range, while San Ysidro is closer to the coast and for this reason there is more developed land.

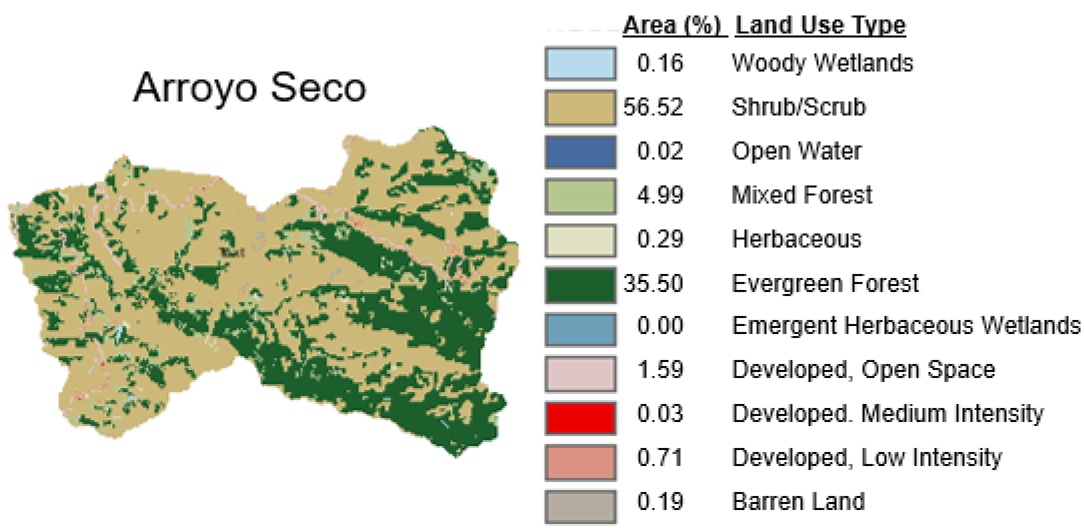

Figure 2. Arroyo Seco land use from 2008 NLCD. (Source: http://www.mrlc.gov/).

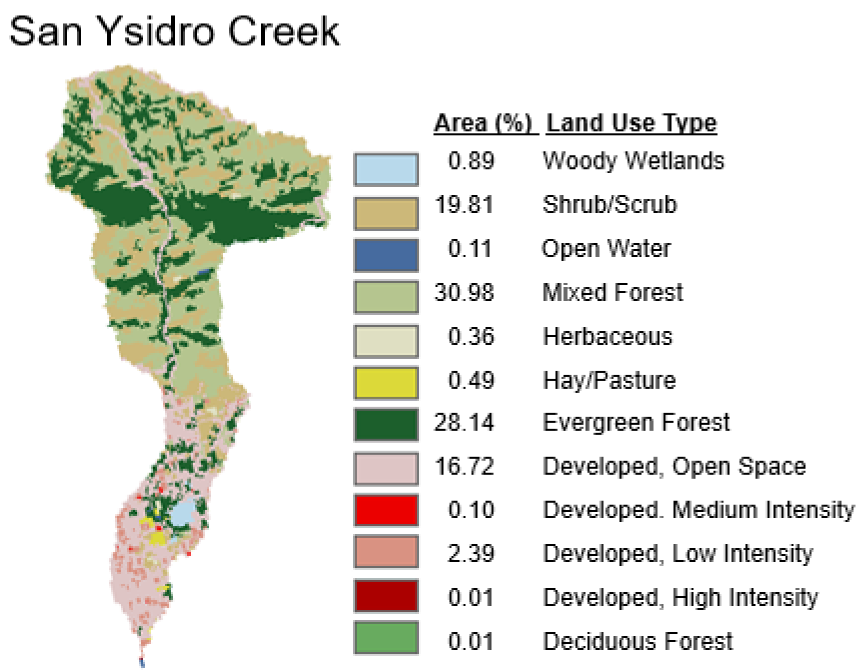

Figure 3. San Ysidro Creek land use from 2008 NLCD. (Source: http://www.mrlc.gov/).

Optimization:

Optimization or auto-calibration finds the best solutions with regard to some conditions. There are three components to optimization; (1) an objective function that mathematically minimizes or maximizes a numeric value and indicates a goodness of fit measure, (2) decision variables are assigned that correspond to the options available to be manipulated, and (3) constraints, requirements imposed on the options. To apply hydrological optimization, a simulation is run to find constraint coefficients for the optimization. A cost function can be added with a set of possible decisions, and solve the optimization model to find the best solution.

Performance evaluation in the calibration and validation process can be evaluated both qualitatively, visually, and quantitatively, with statistical measures. Both methods were applied in this study, the first of which included a visual inspection of the model, then statistical criteria used in the analysis (Feyen et al, 2000). The statistical criteria used in the analysis are the objective functions: the Coefficient of Determination (CD), R^2, and the Root Mean Square Error (RMSE).

These measures are given as:

$$R^2 = \frac{\sum_{i=1}^{n}[O_i - S_i]^2}{\sum_{i=1}^{n}[O_i - \bar{O}_i]^2} \tag{7}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}[O_i - S_i]^2}{n}} \tag{8}$$

Where $O_{,i}$ is the i-th observed value , $S_{,i}$ is the i-th simulated value, $\bar{O}_i$ is the average of the observed values, and n is the number of observations in the considered period.

The CD describes the ratio of scatter plot of the simulated and observed values around the average of the observations. A CD value of one shows that the simulated and observed values match completely; the minimum value is zero and is positive. The RMSE provides a good measure of the average difference between the observed and simulated values, and can be positive or negative (Feyen et al, 2000). A perfect fit is typically indicated by values close to zero.

Figure 4 summarizes the SCE optimization algorithm process in a flow chart. First, parameters are defined for the simulation, observed data is considered from boundary conditions and rain gages. The algorithm generates a random population with selected parameters, uses the objective function, then the evolution process begins with multiple GSSHA simulations. A test for convergence will then provide inundation depths and optimized parameters. If there is no convergence, the evolution process needs to be repeated.

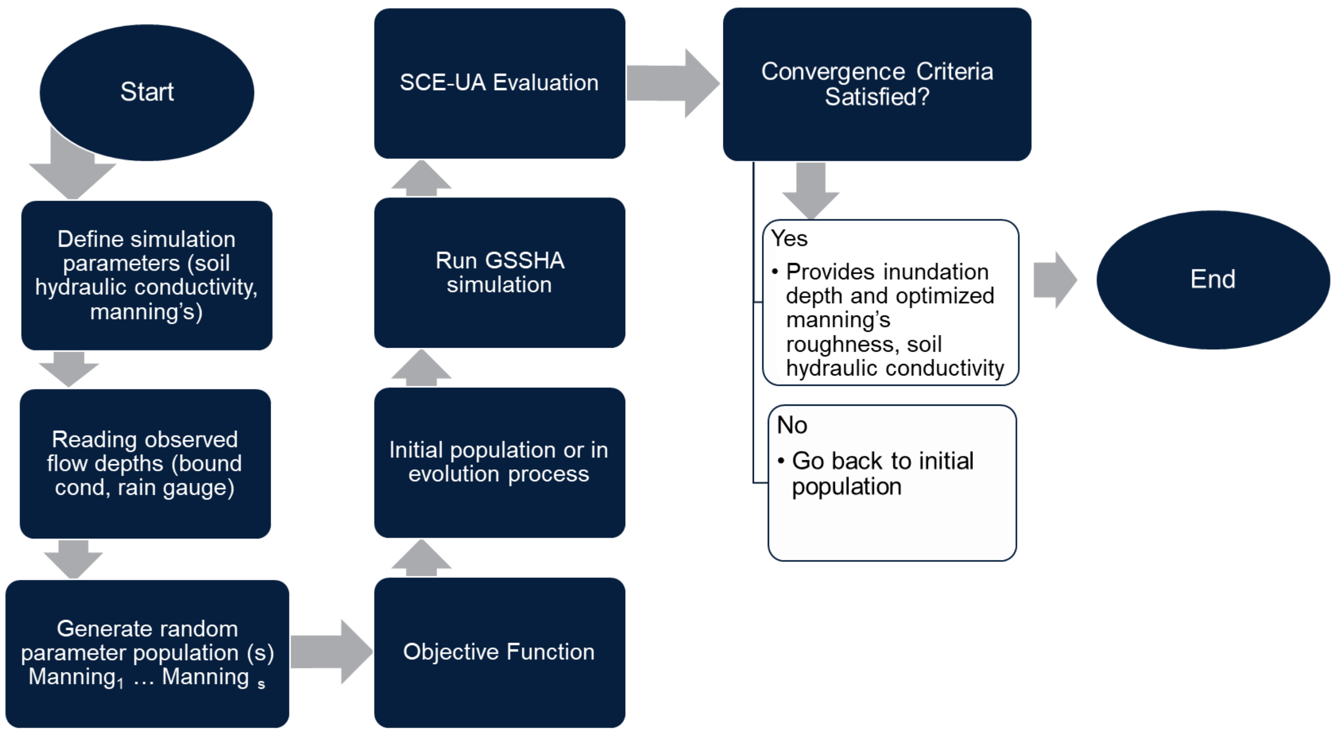

Figure 4. Flowchart on optimization process.

Results and Discussion

Pre-fire Model Calibration

The watershed models were developed with infiltration, surface roughness, and soil moisture. The pre-model calibration was prepared as an event-based simulation that included the 2018 January 9 atmospheric rainfall event. The return period of the event was of 200 to 500 years, implicating a high flow. The source of parametric values based on the Arroyo Seco watershed (Pradhan and Floyd, 2021) was employed due to its proximity to the Santa Barbara watershed. Infiltration average values considered for the pre-fire condition was based on the literature from Pradhan and Floyd, (2021) and GSSHA manual (Table 2).

Average parameter values for Manning's roughness were considered from the 2016 National Land Cover Database (NLCD) the Pradhan and Floyd (2021) and GSSHA defined values and study shown in Table 3. Initial soil moisture was assumed to be uniform across the watershed with value of 0.18.

Table 2. Pre-fire soil infiltration parameter values based on soil texture for San Ysidro model. (Amended: Pradhan and Floyd, 2021).

Soil infiltration parameter	Value
Saturated hydraulic conductivity (cm/h)	0.81
Capillary head (cm)	11.0
Porosity (m^3/m^3)	0.41
Pore distribution index (cm/cm)	0.37
Residual point (m^3/m^3)	0.04
Field capacity (m^3/m^3)	0.2
Wilting point (m^3/m^3)	0.09

Table 3. Pre-fire Manning's roughness parameter values for the routing model. (Amended: Pradhan and Floyd, 2021).

Land Cover Type/ Condition	Manning's roughness value ($s/m^{1/3}$)
Open Water	0.09
Developed, Open Space	0.15
Developed, Low Intensity	0.15
Developed, Medium Intensity	0.15
Deciduous Forest	0.45
Evergreen Forest	0.45
Mixed Forest	0.45
Shrub/ Scrub	0.44
Grassland/ Herbaceous	0.43
Pasture/Hay	0.20
Cultivated Crops	0.20
Woody Woodlands	0.14

Post-fire Model Calibration

On Table 4, the post-fire manning's roughness is reduced based on the post-fire burn condition (Pradhan and Floyd, 2021). Burn severity analyses of satellite coverage data showed that 11% of the area within the burn boundary were unburned, 31% burned with low severity, 56% moderately burned, and 1% burned with high severity. The most common type of burn in the San Ysidro Creek watershed was a medium burn, therefore Manning's roughness is taken as 0.18. Table 5 demonstrates the changed Manning's roughness values according to the burn severity. Soil moisture was assumed to be uniform across the watershed at 0.13. Infiltration parameters changed within the model structure simulations according to the Pradhan and Floyd (2021) post-fire condition equation.

Table 4. Post-fire burn condition for infiltration model. (Amended: Pradhan and Floyd, 2021).

Burned Condition	**Manning Roughness Value (s/m$^{1/3}$)**
No burn	No Change
Low burn	0.2
Medium burn	0.18
High burn	0.15

Table 5. Post-fire Manning's roughness values for infiltration model. (Amended: Pradhan and Floyd, 2021).

Land Cover Condition	**Manning's roughness value (s/m$^{1/3}$)**
Deciduous/Evergreen/Mixed Forest + Medium Burn	0.18
Shrub + Medium Burn	0.18
Grassland + Medium Burn	0.18
Open Water	0.09
Developed, Open Space	0.15
Developed, Low Intensity	0.15
Developed, Medium Intensity	0.15
Deciduous Forest	0.45
Evergreen Forest	0.45
Mixed Forest	0.45
Shrub/ Scrub	0.44
Grassland/ Herbaceous	0.43
Pasture/Hay	0.20
Cultivated Crops	0.20
Woody Woodlands	0.14

Parameter Transfer Results for San Ysidro Creek:

Figures 5 to 7 illustrate the GSSHA simulated discharge for pre- and post-fire conditions for San Ysidro Creek with transferred parameters from the Arroyo Seco watershed (Pradhan and Floyd, 2021). The soil moisture is estimated at 30-m resolution to match the GSSHA model grid resolution. The hydrological models were developed with infiltration, surface roughness, and soil moisture. In this study, three scenarios were modeled with the 09 January 2018 rainfall event; (a) the pre-fire condition without considering the fire effects, underestimating the discharge (Figure 5), (b) the post-fire routing condition developed with a change in surface roughness (Figure 6), (c) the post-fire infiltration condition with a reduction factor of 0.1 (or 90% reduction) in soil hydraulic conductivity (Figure 7). Surface roughness and hydraulic conductivity were reduced according to the burn severity (Pradhan and Floyd, 2021). The purpose of modeling the pre-fire condition was to compare the resulting flood depth to the post-fire conditions to examine the effectiveness of the post-fire reduction factor. The difference between the three models is visually shown south of the watershed with spreading of the flood grid and in max flow depth increasing values from 0.20 meters to 1.60 meters of maximum flow depth. Figure 5 does not consider fire effects and the flood extent does not go all the way downstream (0.2-0.4 meters maximum flow depth). Figure 6 considers a change in surface roughness and the flood extent goes all the way downstream of the watershed with more flow (0.2-0.8 meters) than Figure 5. Then, Figure 6 considers both the change in surface roughness and changes to infiltration, therefore having a larger maximum flow depth (up to 1.6 meters) than the previous figures and reaching the downstream area. Figure 8 shows the observed and the simulated post-fire infiltration condition flow depths closely matching in their flood locations. The southern portion of the watershed that contains developed land with many residential areas was affected the most with flow depths up to 1.60 meters.

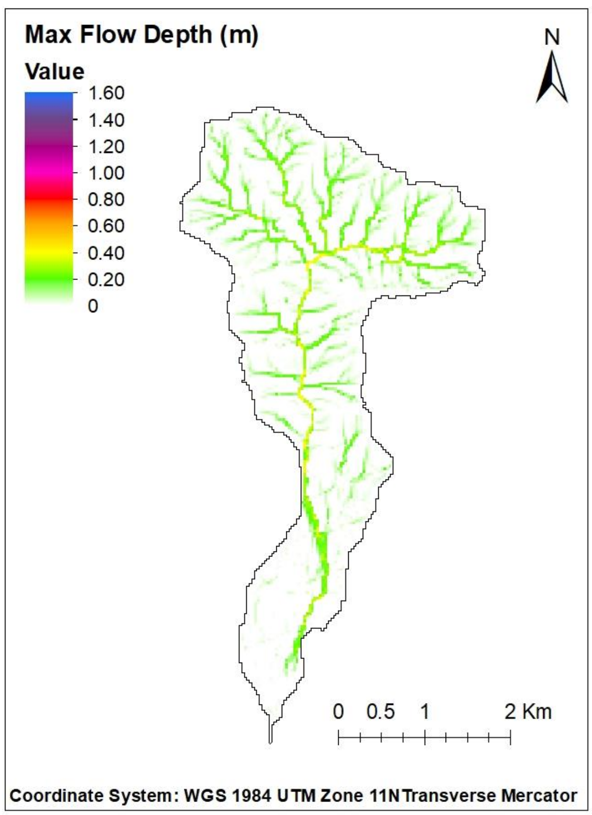

Figure 5. Pre-fire condition without considering the fire effects.

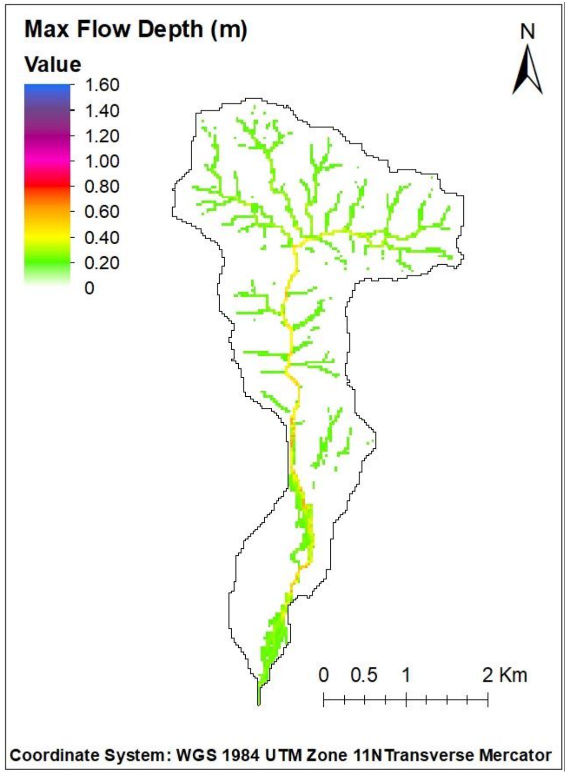

Figure 6. Post-fire routing condition developed with change in surface roughness.

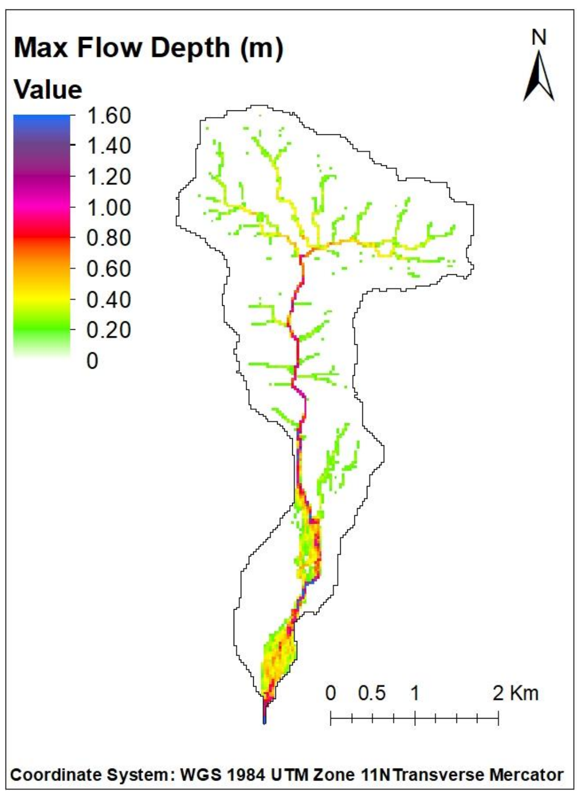

Figure 7. Post-fire infiltration condition with a reduction in soil hydraulic conductivity.

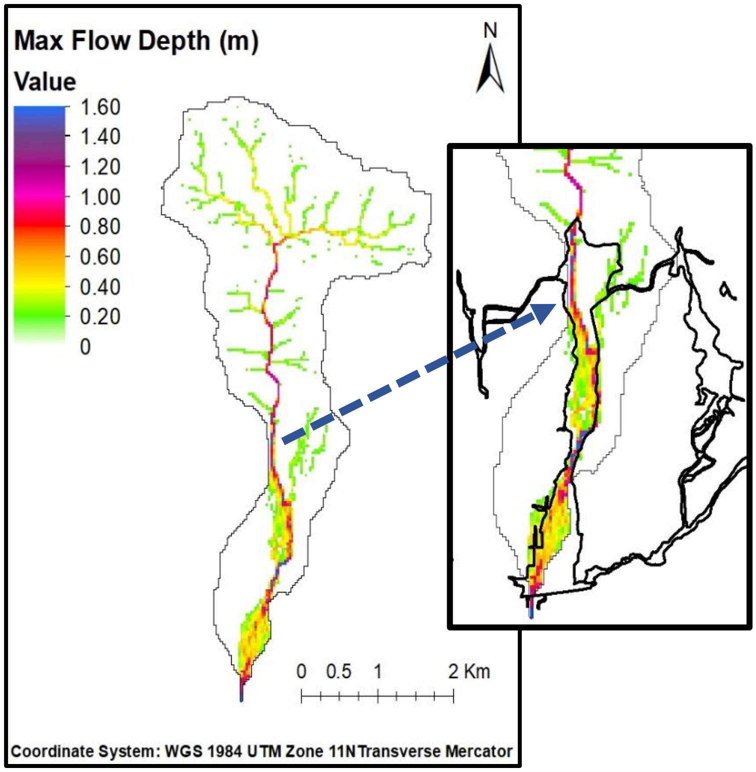

Figure 8. Simulated post-fire infiltration condition compared to observed maximum flow depths.

The illustrations of the different scenarios demonstrate the difference in flood surface elevations where the pre-fire condition has a maximum flow depth of 0.39 meters (Figure 5), the post-fire routing condition, 0.64 meters (Figure 6), and the post-fire infiltration condition, 1.60 meters (Figure 7). Figure 8 shows the simulated model results and the observed inundation boundaries outlined in black. It can be seen that the maximum flow depth increases by an order of magnitude between Figure 11 and 12 showing that a reduction in hydraulic conductivity increases flood surface elevations by an order of magnitude, implying that the runoff generation process is more significant than the routing process in this study.

Different flood depth values were extracted from various locations across the watershed and compared between observed and simulated depths (Figure 9). The observed values were from a small sample size of the entire watershed and then simulated based on the post-fire reduction condition. There is a cluster of points near the origin and one point outside of the range. Future research should include more values from low to high ranges to better define trends.

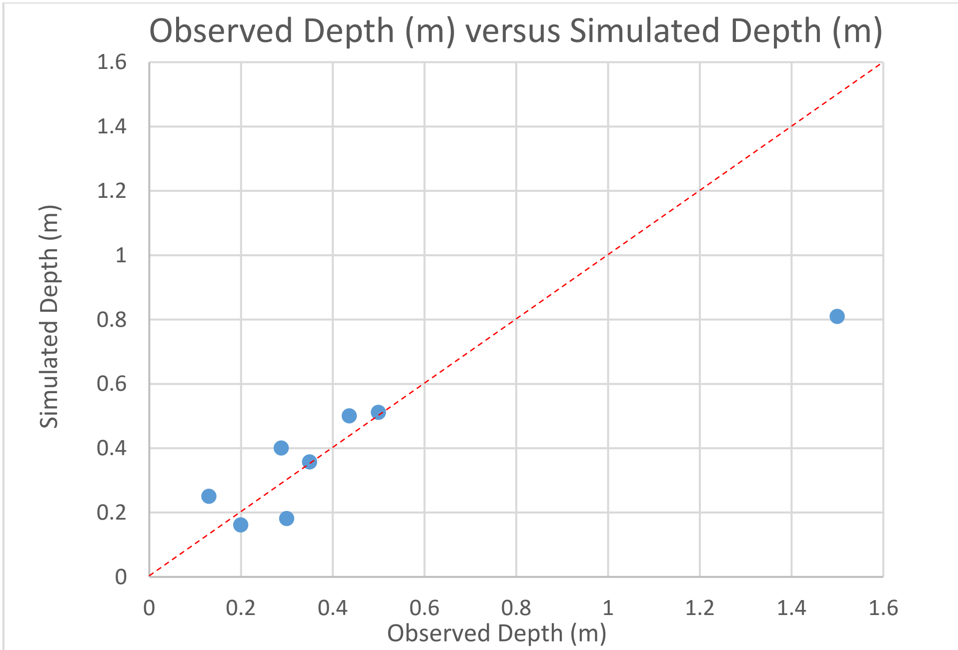

Figure 9. Observed depth versus simulated depth for the San Ysidro Creek of 09 January 2018 flows.

Based on the Pradhan and Floyd (2021) study, the hydraulic conductivity reduction factor was modeled with a 0.1 (or 90% reduction) and the coefficient of determination (R^2) used as the objective function between the observed and simulated values. Donigian (2002) affirms that the coefficient of determination (R^2) values range for assessing flows is to be very good when it is greater than 0.8; good when it is between 0.7 and 0.8; fair when it is between 0.6 and 0.7; and poor when it is less than 0.06. The post-fire reduction factor scenario had an R^2=0.79, and RMSE=0.26 and are considered satisfactory in model performance. The small sample size of observational flow depth values indicates that set of parameters identified were able to represent the hydrological processes.

Optimization Results for San Ysidro Creek:

Hydraulic Conductivity and Manning's roughness were optimized using the SCE method with RMSE as the objective function and it was revealed that the hydrologic response was comparable to the transferred parameters.

Hydraulic Conductivity:

As shown in Figure 10, the hydraulic conductivity reduction factor, Rf_k, was calibrated using the SCE optimization algorithm, RMSE was used as the objective function between the observed and simulated values.

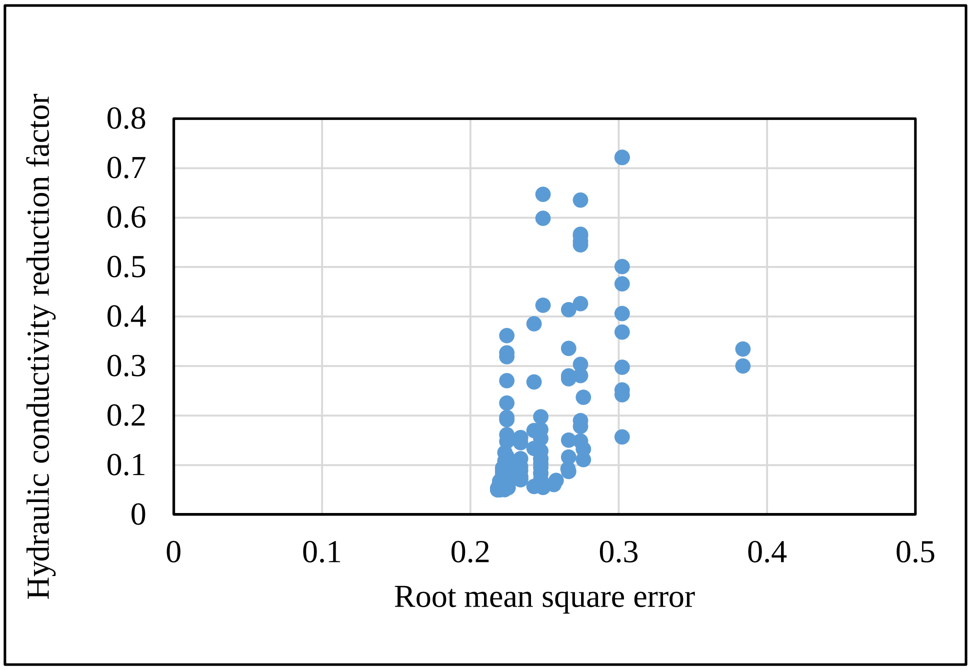

Figure 10. Hydraulic Conductivity Reduction Factor (Rf_k) versus Root Mean Square Error (RMSE) optimization based on SCE optimization algorithm.

Arroyo Seco was calibrated with an Rf_k equivalent to 0.10 (or 90% reduction) which is similar to the calibrated results for San Ysidro Creek. Figure 10 illustrates the relationship between the RMSE and the post-fire hydraulic conductivity reduction factor (Rf_k). In this post-fire scenario, the Rfk is equivalent to a 0.05 (or 95% reduction) in hydraulic conductivity, where RMSE reaches an equilibrium between 0.2 and 0.3 demonstrating the impact of the fire on the land cover. Generally, the closer the RMSE is to 0, the more accurate the model is. The RMSE is comparable to that of the transferred parameters, reiterating that there was a reduction in hydraulic conductivity.

A study done by the USGS assessed core samples with tension infiltrometer measurements showed significant decreases in field hydraulic conductivity in burned areas relative to unburned areas therefore confirming the reduction in hydraulic conductivity results of this study (Ebel and Moody, 2020). The infiltration rate is a function of hydraulic conductivity, implicating that less water is infiltrating, therefore causing higher flow depths. The heating of organic matter in medium severity burns may be attributed to water repellency. Sorptivity directly relates water repellency to infiltration (Shillito et al., 2020).

Manning's Roughness:

Manning's roughness, n, was calibrated using the SCE optimization algorithm, the root mean square error (RMSE) was used as the objective function between the observed and simulated values (Figure 11).

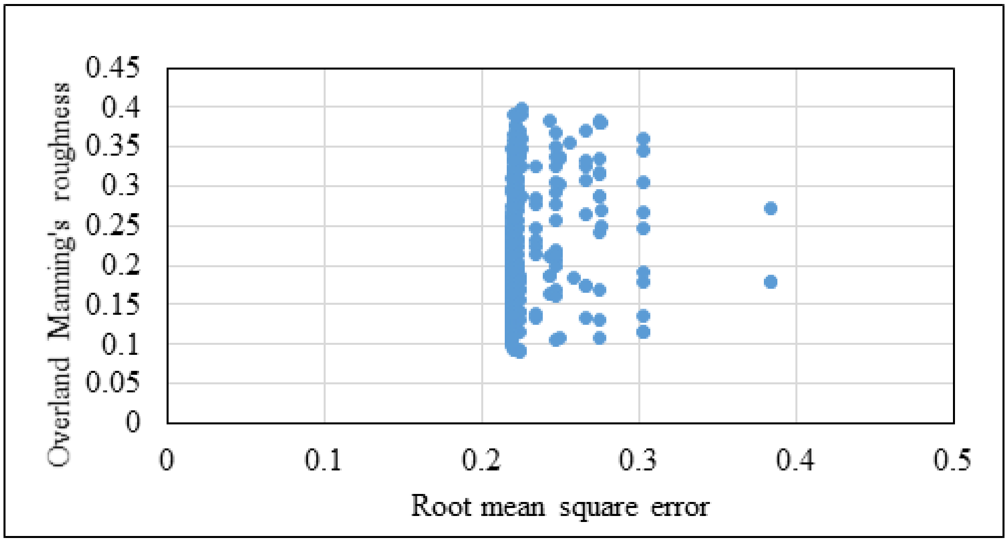

Figure 11. Manning's roughness versus Root Mean Square Error (RMSE) optimization based on SCE optimization algorithm.

Manning's roughness was considered for shrub land cover with ranges from 0.09 to 0.45. The RMSE has a cluster of points from 0.2 to 0.4, with a concentration of points at 0.22. There is not much sensitivity in manning's roughness as there was in the Rf_k. Surface roughness may change after a wildfire by the consumption of vegetation, litter, and duff, and by the deposition of an ash layer (Moody et al., 2013). The non-uniformity in the spatial distribution of sediment sources can change the transport process (Santi et al., 2008). Essentially, material and ashes can move with water causing changes in runoff patterns and sediment transport. Change in land cover is a dynamic process after fires, which may indicate surface roughness being a less sensitive parameter. Furthermore, the steep terrain and riprap stability may be factors to consider when computing hydraulic conditions. Manning's roughness is highly dependent on the flow depth/mean size of bed particle. The change in Manning's roughness from a very shallow depth (e.g., water depth is of same magnitude as mean size of bed particle) to not shallow depths (e.g., flow depth/mean size of bed particle > 30) can be of an order of magnitude (Brown and Clyde, 1989).

Similarity in both transferred and optimized parameters improved calibration and reduced the level of uncertainty in simulation runs. The San Ysidro Creek and Arroyo Seco watersheds had similar conditions and therefore had similar hydrologic responses following intense wildfire events. The parameterization methodology in this study can be further applied for ungauged or poorly gauged watersheds.

Assumptions and Limitations:

The stream gages near San Ysidro Creek were burned during the Thomas fire, hence the lack of flood elevations and discharge datasets for the pre- and post-fire flood event. The maximum flow depth, h, was estimated from the run-up on the downstream side of trees and mudlines on structures acquired from the Kean et al. (2019) study. Measurements of soil-hydraulic properties were unavailable, therefore alternative methods were used for parameterization. Parameters from the Arroyo Seco watershed were first calibrated using the Nash-Sutcliffe efficiency as the objective function for pre- and post-fire events. Then, parameters were transferred using the calibrated values and calibrated once again using RMSE as an objective function.

Conclusion and Recommendations

The hydrologic behavior of the San Ysidro Creek watershed was simulated using GSSHA after different scenarios (pre- and post-fire conditions) with transferred parameters from a similar, nearby watershed. The different scenarios accounted for the following identified parameters: Manning's roughness and the hydraulic conductivity reduction factor. Performing the model validation demonstrated a good representation of the observed data. Auto-calibration was performed using the SCE method for both parameters and it was found the hydrologic response was comparable between the transferred parameters and auto-calibration.

The three pre- and post-fire scenarios demonstrated the differences of hydrologic response (changes in depth and areal extent) depending on different factors considered when applying GSSHA. The pre-fire condition did not consider fire effects and had little flow depth that did not extend downstream. Whereas, the post-fire routing condition that considered a change in surface roughness extended downstream and had more flow depth. The post-fire infiltration condition considered both the change in surface roughness and infiltration and showed the most significant changes in flow depth. It was established that although both parameters were sensitive, the hydraulic conductivity reduction factor was significantly more dominant.

Understanding hydrological processes in the development of pre-fire and post-fire models is crucial for emergency assessment. This study provided an organized physics-based framework that characterized different hydrological processes and provided a methodology for future studies for ungauged and poorly gauged watersheds.

Future research should focus on enhancing the understanding of post-fire soil hydraulic responses and modeling capabilities by improving post-fire field measurements to help validate models. Attention should be devoted to soil and land data collection as the data is important in characterizing post-fire hydrology. Since wildfires are increasing in frequency, multiple methods of field measurements including remote sensing should be explored in the years that follow. Laboratory tests on hydraulic conductivity and manning's roughness could provide a parametric range for future studies.

Additional studies on Manning's roughness should be applied to test for uncertainty. Likewise, routing conditions with similar topography should be considered. An assessment of the extent of similarity in parameter transfer should be evaluated to understand when parameter transfer is appropriate. Finally, GSSHA can be implemented for planning structural designs in flood-prone areas for communities to be protected.

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