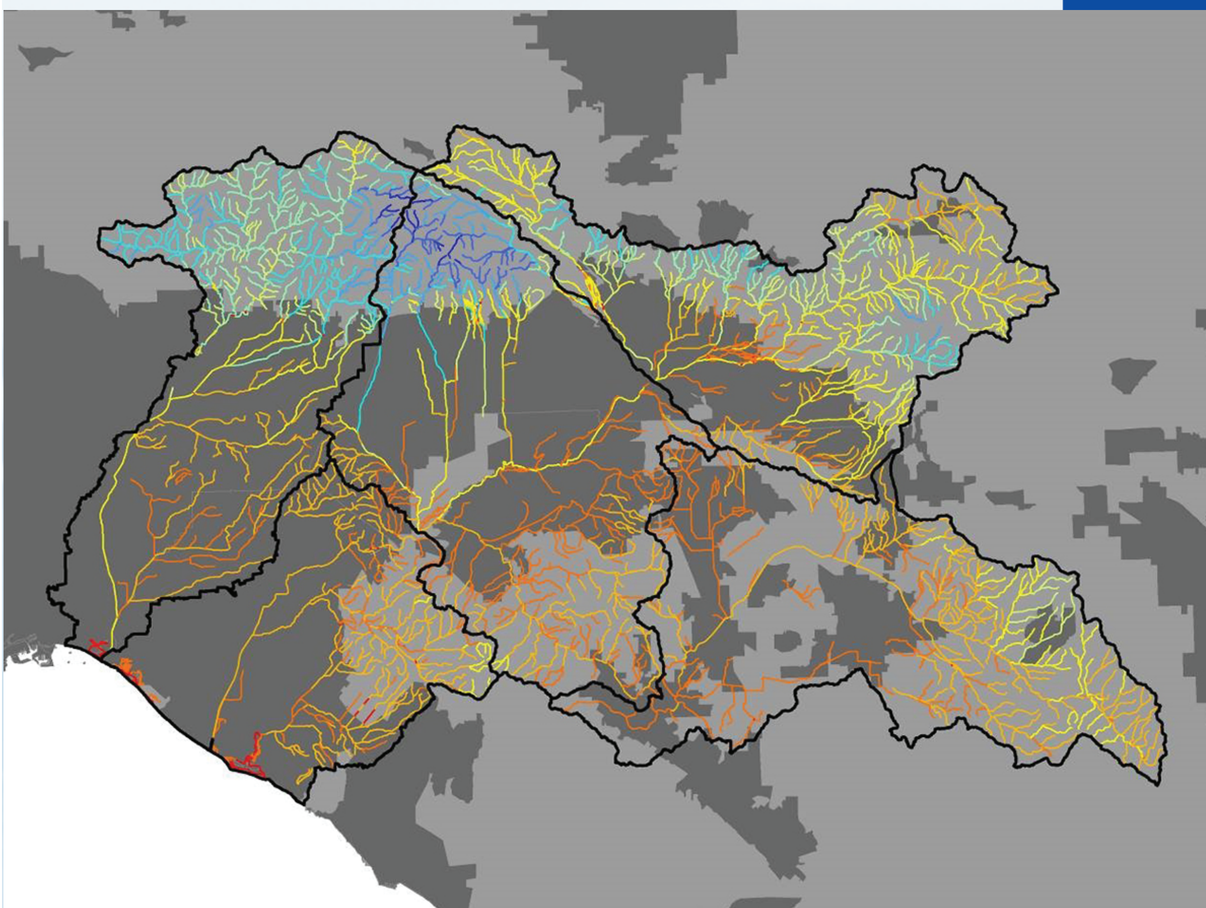
Mapping of Non-Perennial and Ephemeral Streams in the Santa Ana Region



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SCCWRP Technical Report 1012

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EXECUTIVE SUMMARY

Overview

Ephemeral streams lack surface flow for most of the year and are common features of hydrologic networks in arid regions of Southern California. These streams drain large areas of watersheds and can greatly influence the quantity and quality of downstream waters. However, ephemeral streams are generally excluded from regional assessment programs due to lack of assessment tools. For example, there are no reliable maps that show where ephemeral, intermittent, or perennial streams occur in Southern California. The assessment of non-perennial streams, in addition to traditional monitoring of perennial waters, is critical for developing a complete picture of watershed health.

Identifying the locations and extents of ephemeral streams is the first step towards more comprehensive assessments. Existing maps do not adequately represent which streams are ephemeral vs. those with longer flow durations. Knowing the extent and locations of these streams is important to evaluating the ability of existing assessment tools to characterize hydrologic and ecological conditions and to support development of new assessment tools.

Stream maps that are currently available are insufficient to describe the extent and location of ephemeral streams. Existing map products are typically created by manual photointerpretation or based on estimates of flow accumulation with elevation changes. Maps produced using both methods will under-represent ephemeral streams or provide inaccurate locations. Streams may not be visually identified with photointerpretation or maps based on elevation layers may have poor sensitivity in low gradient environments.

The Santa Ana Regional Water Quality Control Board (RWQCB) has recently investigated the use of stream periodicity models to map and describe ephemeral streams in Southern California. These models improve on traditional mapping methods by estimating the likelihood of perennial vs. ephemeral flow at every stream reach in the drainage network. Building on earlier efforts in the San Diego region, this report summarizes efforts to develop and apply stream periodicity models in four watersheds of the Santa Ana region, plus the adjacent San Gabriel watershed. The objective of this application is to better characterize non-perennial streams in this highly developed watershed, in addition to understanding the abilities of existing tools to characterize flow conditions in different watersheds.

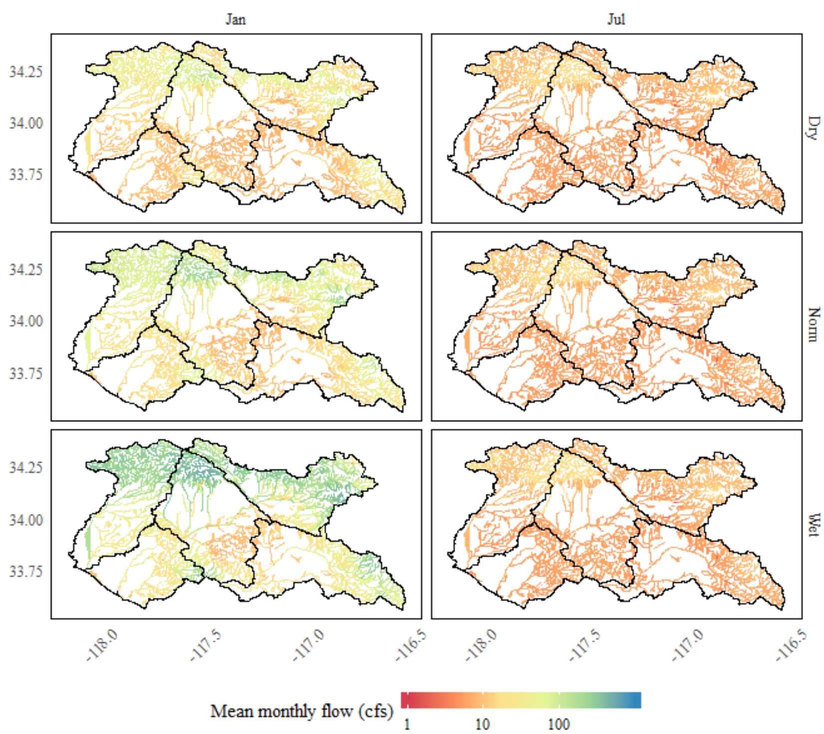
Key findings and products

Historic (pre-developed) flows were estimated by modeling stream discharge at 58 reference gauges from arid regions of southern and central California. This model predicts mean monthly flow under wet, normal, and dry conditions, based on watershed characteristics (such as area and geology) and climate data. Because the model was calibrated with reference gauges, predictions reflect undisturbed conditions at catchments that have undergone conversion to urban or agricultural uses. A second model was then developed to estimate likelihood of change from historic conditions (i.e., inflated or diminished flows) based on land cover. Both models were applied to all stream segments in the Santa Ana region, providing maps showing historic and present-day hydrologic conditions.

Ephemeral streams are likely to change from year to year

Estimates of stream flow vary considerably both throughout the year, and across climate conditions. Static classes of flow duration (e.g., "perennial," "non-perennial") are unlikely to characterize a stream accurately. A probabilistic approach (e.g., "likelihood of flow") may provide a more meaningful way to characterize flow duration.

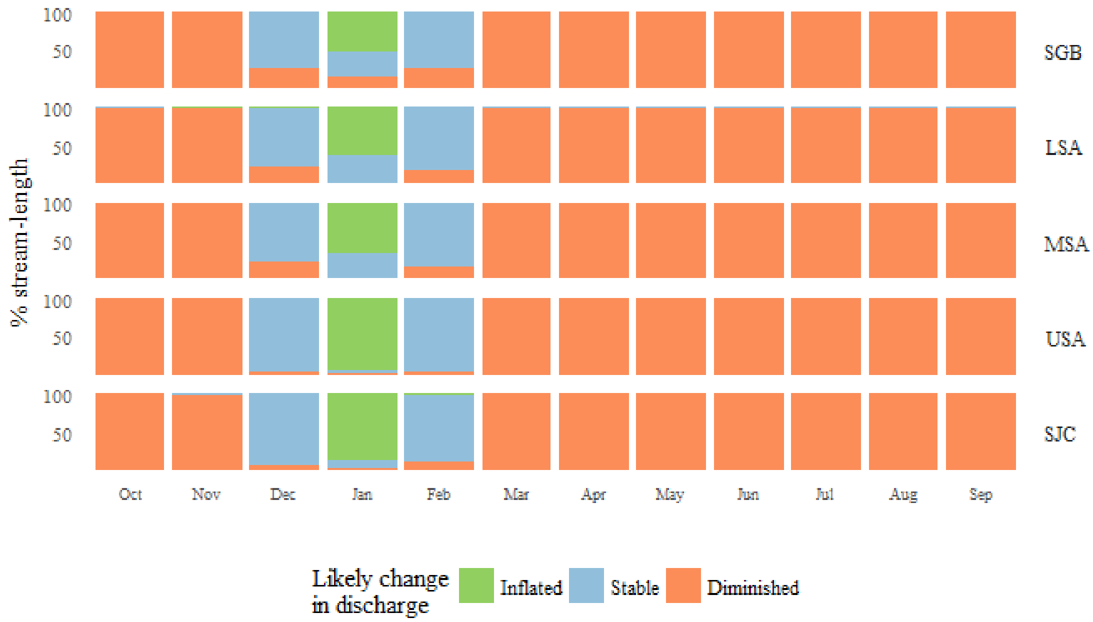
The predictive models were able to produce maps of the relative likelihood of short vs. long flow duration. Somewhat higher estimates of flow were predicted than is typically encountered in undeveloped portions of the region—particularly during low-flow conditions. However, the relative patterns were correct, indicating that the maps and models are most useful for estimating relative extents within the Santa Ana region.



Estimates of stream flow under reference conditions vary by month, as well as climatic conditions.

Developed land use leads to reduced stream flow in most years

Models estimated widespread changes in streamflow from historic conditions. Flows may be reduced at most streams for most of the year, although some streams may have inflated flows in winter months. These changes are typical of urbanization, where impervious surfaces increase peak flows and decrease baseflows, leading to a flashier hydrograph. Conditions in wet years may be somewhat more stable than normal or dry years.



In all watersheds, stream-flow reduction (red) from historic levels may be pervasive for most months of the year. Stable conditions (blue) may be more common in winter months, while inflated flows (green) only occur during the winter. SGB: San Gabriel; LSA: Lower Santa Ana; MSA: Middle Santa Ana; USA: Upper Santa Ana; and SJC: San Jacinto.

How can these data support management decisions?

Maps and models of stream flow dynamics can support a number of management decisions (see section 7). For example:

- *Prioritize streams for monitoring of hydromodification impacts.* Maps can identify areas where modification has likely been altered, which can be verified with follow-up hydrologic or habitat monitoring.
- *Set targets for flow management*. In some cases, historic flows may be an appropriate target to restore biological condition or other beneficial uses.
- *Provide evidence on causes of impairment related to flow alteration*. Maps and models can be used in streamlined causal assessments to determine if flow alteration is a supported cause of poor biological condition.
- *Select assessment tools appropriate for local flow conditions*. Certain assessment tools (e.g., benthic macroinvertebrates, algae) are best suited for perennial or intermittent streams,

while ephemeral streams are best evaluated with other tools (e.g., riparian plants). Maps will let monitoring programs know which tools will be best for the task at hand, prior to any site visits.

- *Forecast the impacts of climate change or land use conversion*. Models allow predictions of changes to stream flow under different climatic regimes or impervious cover. These predictions can prioritize areas requiring protection or mitigation. Similarly, these tools could help evaluate the impacts of changes in water management, such as increased stormwater capture or water recycling.

Because models are spatially explicit, all these decisions can be made on a site-specific basis—without the costs typically associated with developing site-specific hydrologic models.

Recommendations

The development of flow predictions under different land use and climate scenarios for the Santa Ana region is a first step towards more holistic stream assessment in Southern California. Additional steps can be taken that focus on key components of this work to expand applications beyond the Santa Ana region:

- *Improved predictions of low flows*. Low flows were likely over-estimated in much of the region, and relatively insensitive to climatic variability. This outcome is likely a consequence of the scarcity of intermittent and ephemeral streams in the calibration data. Incorporation of new data sources (e.g., water-level loggers) from these stream-types is likely to improve predictions of low flows.

- *Improve estimates of altered flow*. Models estimated the likelihood of flow alteration, but not the severity. The finding that alteration was widespread begs questions about the magnitude of change, and whether these alterations are having a likely impact on aquatic life or other beneficial uses. Incorporation of data about diversions, dam management, and other activities that affect flow could improve models.

- *Integrate with other stream flow assessment methods*. Maps could be used in tandem with other stream flow classification methods, such as those based on field indicators. Stream-flow maps are likely to enhance these methods for applications where classifications are needed (e.g., Federal jurisdictional determinations). The integration of multiple methods warrants further investigation.

- *Support use of data products*. The impact of this work could be extended if additional tools are developed that improve the communication of results. In particular, interactive applications could be developed that allow users to better visualize projected impacts within the regions. These tools could include online map applications or specific software tools that allow a more comprehensive evaluation of the results.

Products

Shapefiles and statistical models may be downloaded here: ftp://ftp.sccwrp.org/pub/download/TMP/RaphaelMazor/SantaAnaflowmodels.zip.

Statistical models

Two statistical models (as R objects) to predict 1) historic (reference) stream flows and 2) likelihood of inflated or diminished flow under present-day conditions.

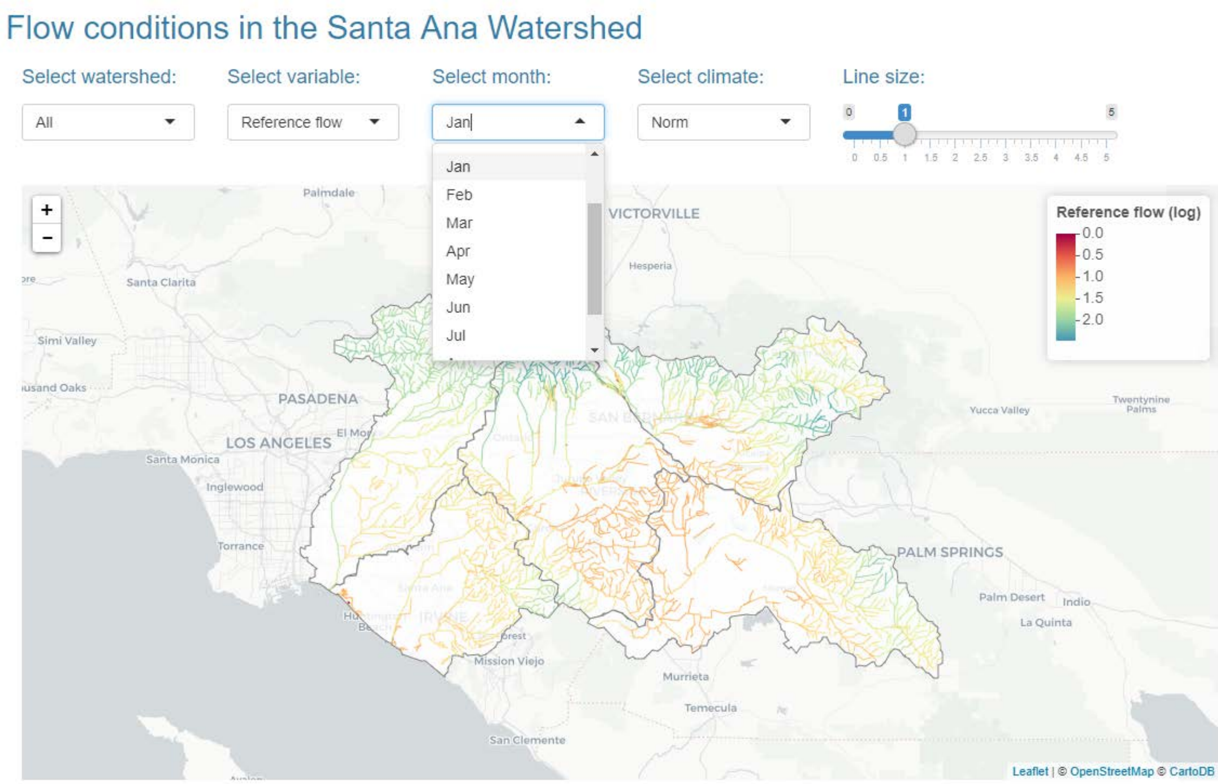
Geodatabase of model predictions

Two geodatabases that represent predictions for every stream segment in the Santa Ana region were created for 1) historic (reference) stream flows and 2) likelihood of inflated or diminished flow under present-day conditions:

- Flow estimates under reference conditions in each month for dry, stable, or wet conditions
- Likelihood of stream flow inflating or diminishing under anthropogenic conditions for each month under dry, stable, or wet conditions.

Interactive web application

An interactive web application is provided to demonstrate how the model results can be used to support management decisions. This application can be used to evaluate results for reference conditions and expectations of flow change. Individual watersheds and stream estimates can be evaluated by zooming and hovering the mouse over a location. Please visit the application at https://beckmw.shinyapps.io/santa_ana_flow/



A screenshot of the interactive web app for viewing model results.

TABLE OF CONTENTS

1. OVERVIEW

Non-perennial streams are defined as streams that lack surface flow for at least several days per year in typical years. Non-perennial streams comprise the majority of streams in southern California, but we have little information on which streams are non-perennial, nor how to characterize the diverse flow regimes non-perennial streams exhibit. Consequently, it is difficult for water quality programs to target waterbodies of interest, nor is it possible to be sure where policies that apply to perennial streams may be implemented.

Updated hydrologic maps are needed because existing maps (such as those provided in the National Hydrography Dataset, NHD) do not adequately represent the location and extent of non-perennial streams. Because few non-perennial reference streams have been sampled throughout California, their hydrology and biology are not well described (particularly within the Santa Ana watershed). Preliminary research has shown that some non-perennial streams in San Diego are ecologically similar to perennial streams, suggesting that existing assessment tools used for perennial streams (such as the California Stream Condition Index) may be adequate for some types of non-perennial streams. More data from a range of minimally disturbed non-perennial streams is needed to determine the extent to which existing assessment tools can be used for different types of non-perennial streams, particularly in regions outside San Diego.

The goal of this project is to build upon previous work, and, refine and apply the stream periodicity model created for San Diego Regional Water Quality Control Board (RWQCB 9) to watersheds encompassed by the Santa Ana Regional Water Quality Control Board (RWQCB 8), in order to, produce a map of likely non-perennial streams and associated stream flow metrics. The NHD and/or NHDPlus HydroDEM will be utilized as the base stream network for the model.

2. TASKS

This project involved two tasks: 1) calibration and validation of models to predict historic (i.e., reference) flows, and 2) calibration and validation of models to predict likelihood of flows changing historic conditions. The steps for each task are described below.

1. Re-calibrate the stream periodicity model to RWQCB 8, using NHDPlus flowlines as the base stream network. This model will be based on reference sites to predict reference streamflow characteristics. This task will be referred to as the *reference* model from this point forward.

    - Deliverables:

        - Model to predict reference streamflow characteristics in Region 8 (R object), with appropriate documentation and metadata.
        - Model outputs, registered to NHDPlus flowlines (GIS layer), with appropriate documentation and metadata.
        - Assist SCCWRP in developing a technical memo that summarizes model performance, reference streamflow characteristics in regions of

interest within the Santa Ana watershed, and comparison of model predictions to field data.

2. Pilot incorporating anthropogenic factors into a "dirty" model to predict current conditions in hydrologically altered watersheds. This task will be referred to as the *anthropogenic* model from this point forward.

    - Deliverables:

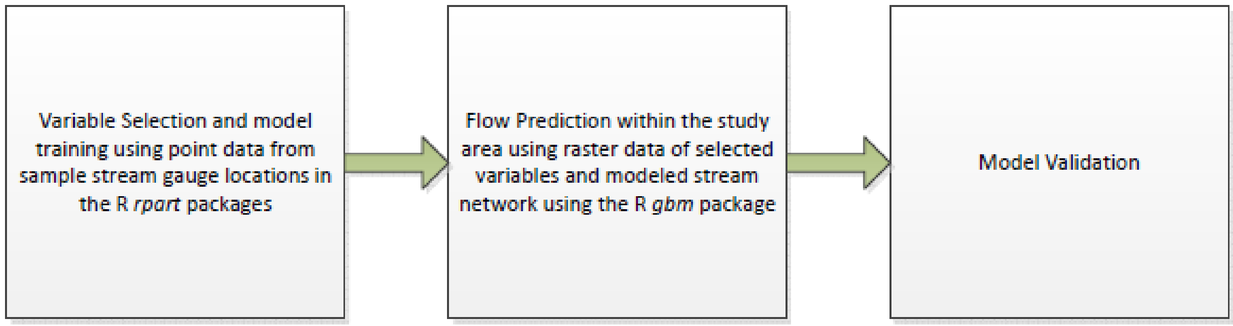
        - Pilot "dirty" model to predict current streamflow characteristics in Region 8 (R object), with appropriate documentation and metadata.

        - Dirty model outputs, registered to NHDPlus flowlines (GIS layer), with appropriate documentation and metadata.

        - Assist SCCWRP in developing a technical memo that summarizes dirty model performance, current streamflow characteristics in regions of interest within the Santa Ana watershed, comparison of dirty model predictions to field data, and comparison of dirty and reference model outputs.

3. Reference Model Methods

3.1 General Process Overview



3.2 Gauge Selection Process

Fifty-eight stream gauges with minimal human disturbance that were active for at least one full month within the target period (1981-2012) were selected to train the reference model (Figure 1). Of 58 these gauges, 4 fall within the Santa Ana watershed. The remaining 54 gauges that fall outside of the Santa Ana watershed are located in areas with similar landscape and climate characteristics. Areas with similar landscape and climate conditions were identified using United States Geologic Survey's (USGS) hydrologic landscape region (HLR) data. For example, all HLR gauges were in xeric regions with low precipitation and high temperatures.

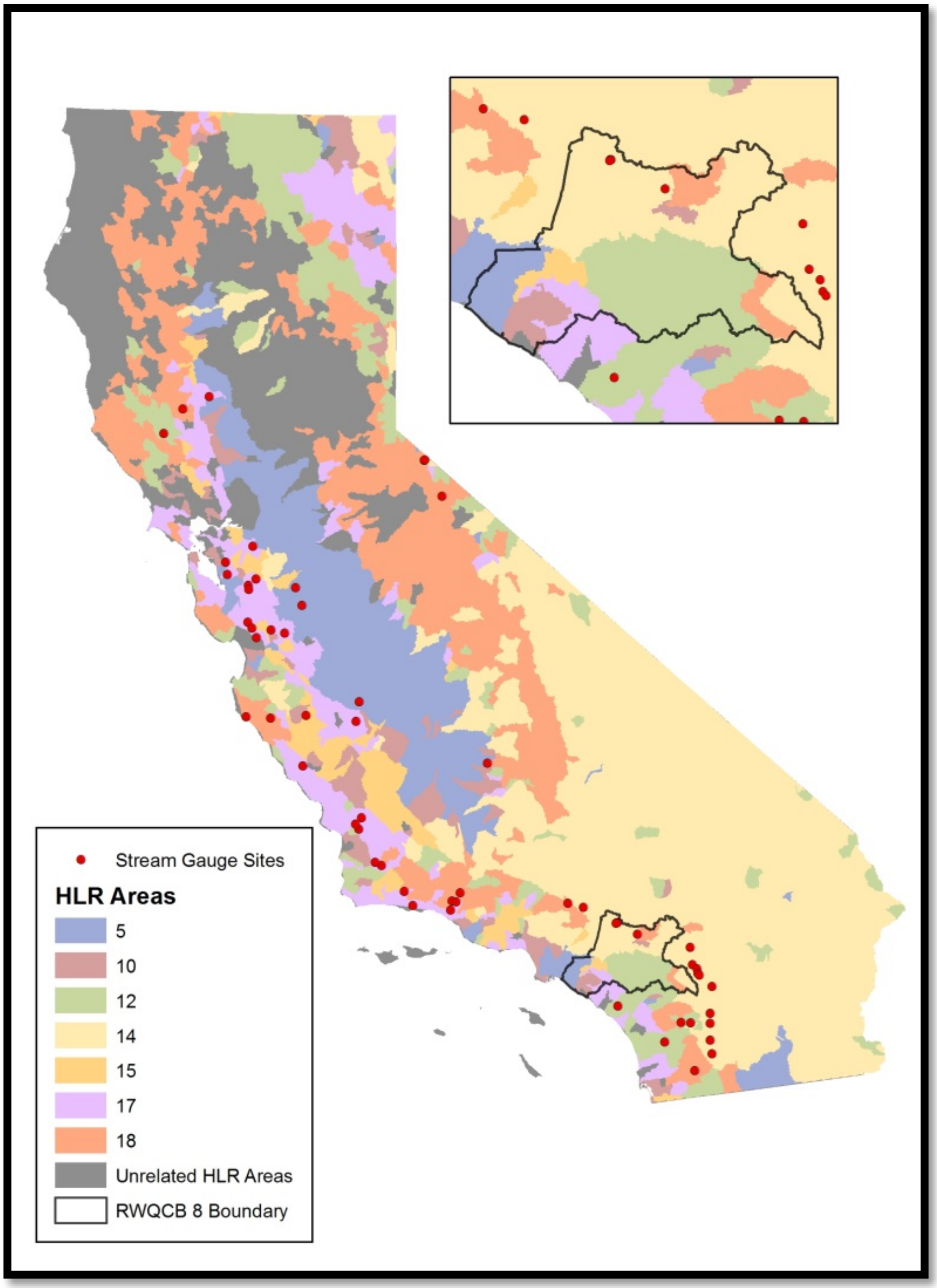


Figure 1. Map of gauges selected for model training.

A decision tree for the process of classifying gauges as reference or non-reference is shown in Figure 2. This decision tree identified reference sites suitable for modeling based on the absence of landscape-level factors that could alter hydrology (e.g., impervious cover, dams), as well as presence of a long-term flow data set.

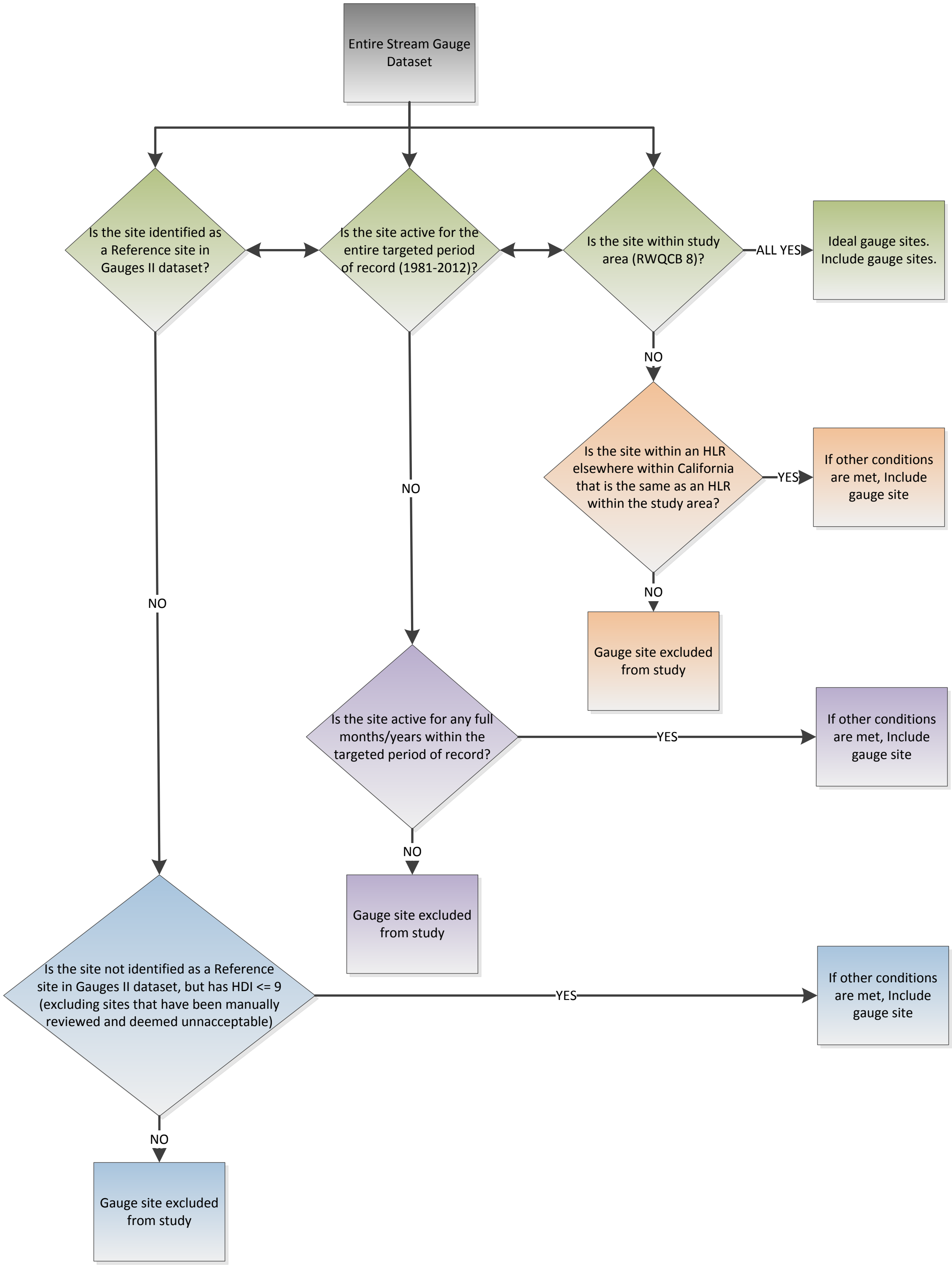


Figure 2. Decision-tree showing how gauges were classified as reference or non-reference, adapted from Falcone et al. (2010). HDI is the Hydrologic Disturbance Index, a measure of landscape-level sources of hydrologic alteration (e.g., presence of dams or impervious cover).

3.3 Included Stream Features

The NHDPlus dataset was used as the base dataset of streams for this project. Streams have been selected from within the NHDPlus dataset if flow direction is applied to the NHDPlus flowlines. In order to generate raster streams to be used as the basis for the variables generated and used in the project, it was required that the streams selected have a noted flow direction. Features are identified as having a flow direction (initialized) within the NHDPlus flowlines if the "FLOWDIR" field is populated with the attribute "With Digitized." However, this identifies streams assigned flow direction within vector flowlines and raster data is needed to process variables for the model. In order to generate raster streams that align fairly well with the length of the NHDPlus initialized flowlines, streams were created using the NHDPlus HydroDEM flow accumulation layer. The NHDPlus HydroDEM is a hydrologically modified digital elevation model from which the flow accumulation layer is generated, "which contains the number of cells within the raster processing unit draining to each cell within the raster processing unit" (United States Geologic Survey 2016). The following equation was applied to the flow accumulation raster grid in order to extract raster cells that correspond to the NHDPlus initialized flowlines: Con (FlowAccumulationRaster > 50, 1). Using this method, 98% (6,327 km) of the NHDPlus-initialized vector flowlines are captured within the study area.

3.4 Flow Metrics

Reference predictions model mean monthly stream flow (cubic feet per second (cfs)) for every month of the year under typical normal year (median: 10.56 inches mean annual rainfall), typical wet year (16.18), and typical dry year (7.50) conditions.

3.5 Variable Selection Process

Eighty-eight landscape and climate variables were included in the variable selection process. The source of all landscape variable data is the USGS Gages II (Falcone 2011) dataset while the source of the climate variable data is the Prism Climate Group (2014).

R's rpart package was used to develop a classification tree which attempted to fit an optimal number of trees to the proposed data using all 88 original environmental variables, including: ppt_ws_3mo, tmean_3mo, etc. (Table 1, Figure 3). The results of this analysis provided a measure of variable importance, which is a sum of the "goodness of fit measures for each split for which it was the primary variables" (Therneau and Atkinson 2015). These measures of importance were scaled to sum to 100 by the rpart package.

Using this method, 26 of the original 88 variables were selected as most important. Of the 26 selected variables, those with high levels of correlation ($r >= 0.75$) were addressed to avoid multicollinearity (via Pearson correlation matrix), removing only those with lowest variable importance from the correlated pair. This process removed 11 variables, leaving 15 variables to be used in subsequent model training (Table 1, Figure 3).

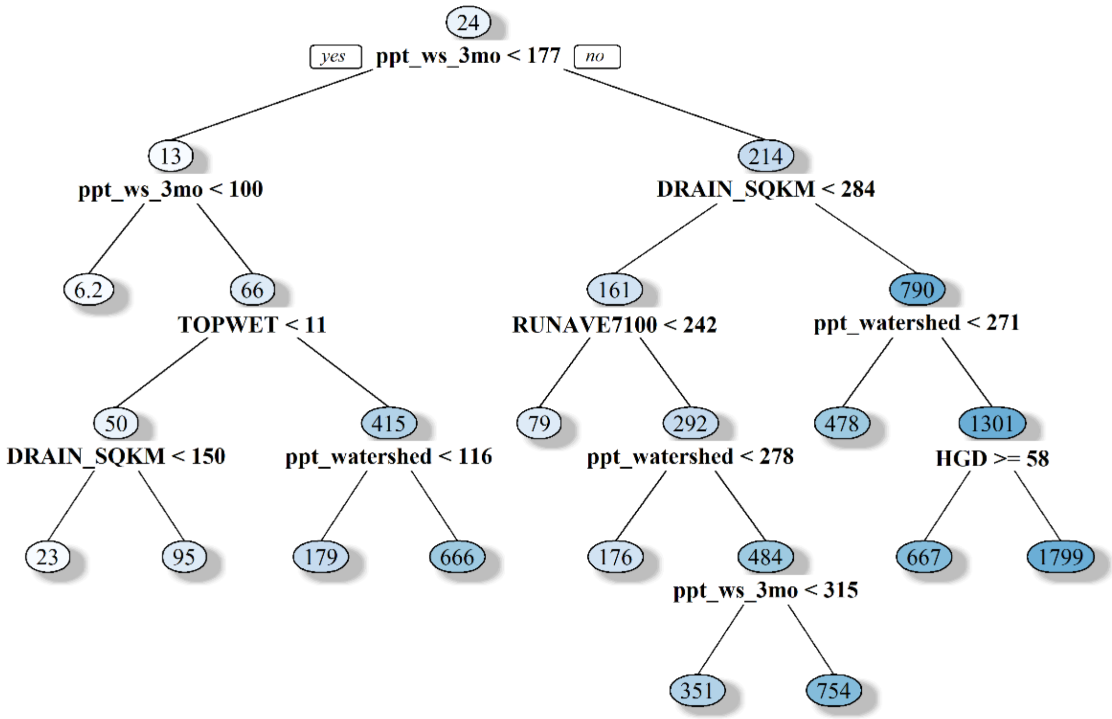


Figure 3. Example of a regression tree created with the rpart package in the R statistical software language. The tree shows one example using the fifteen selected variables in Table 1 to predict mean monthly stream flow (cfs). The estimated stream flow is shown above the split for each branch of the tree, where the split is defined by a specific value for each predictor. The final model is an average of 500 individual regression trees.

Table 1. Final list of variables selected to train the reference model along with their relative importance within the model; higher values indicate greater importance.

Variable Name	Description	Relative influence
ppt_ws_3mo	Three-month mean of monthly precipitation of the upstream drainage area.	24.1
tmean_3mo	Three-month mean of monthly mean temperature of the upstream drainage area.	16.6
DRAIN_SQKM	Drainage area in square kilometers above a site.	10.7
ppt_watershed	Monthly mean precipitation of the upstream drainage area.	7.4
RFACT	Rainfall and Runoff erosivity factor ("R factor" of Universal Soil Loss Equation); average annual value for period 1971-2000.	7.0
ELEV_MEAN_	Mean elevation of upstream drainage area.	5.1
CaO_pct	Percentage of upstream drainage area covered by rock with CaO.	4.9
TOPWET	Topographic wetness index, ln(a/S); where "ln" is the natural log, "a" is the upslope area per unit contour length and "S" is the slope at that point.	4.1
HGD	Percentage of soils that have very slow infiltration rates; these soils are clayey, have a high-water table, or have a shallow impervious layer.	3.7
RUNAVE7100	Estimated watershed annual runoff, mm/year, mean for the period 1971-2000.	3.4
ASPECT_EASTNESS	Mean aspect "eastness" of the upstream drainage area. Ranges from -1 to 1. Value of 1 means watershed is facing/draining due east, value of -1 means watershed is facing/draining due west.	2.9
HGB	Percentage of soils in the upstream drainage area that have moderate infiltration rates; these soils are moderately deep, moderately well drained, and moderately coarse in texture.	2.9
STREAMS_KM	Stream density, km of streams per watershed km^2, from NHDPlus streams	2.7
PERDUN	Dunne overland flow, also known as saturation overland flow.	2.3
RRMEAN_30M	Dimensionless elevation - relief ratio, calculated as (ELEV_MEAN - ELEV_MIN)/(ELEV_MAX - ELEV_MIN).	2.2

3.6 Raster Preparation

Raster files were collected for variables that were selected as predictors during the variable selection process. All raster files were clipped to the same area in terms of columns and rows, and were resampled using ArcGIS 10 BILINEAR resampling technique for surfaces/continuous data (e.g. slope) to the same 30m pixel size. Data sets were projected to the NAD 83 Albers (meters) project. All data sets were clipped to the same region of study (Figure 1) (Mazor et al. 2015).

3.7 Model Training and Predictions

Generalized boosted modeling (gbm) is an iterative machine-learning technique for regression and classification, which produces an ensemble of regression trees to make unbiased predictions for novel data. Unlike traditional tree-based methods (e.g., random forest), particularly good models within the ensemble are “boosted” so that they have a larger influence than individual models with weak performance (Elith et al. 2008).

Using the gbm.step package in R, the final 15 variables were used to train the model against mean monthly flow across the 30-year data time span (i.e., 1981 to 2012). The trained model was applied to all stream segments ($30m^2$) using the predict.gbm function in R to predict stream flow for these unknown flow locations, using a set number of trees in the boosting sequence.

3.8 Model Validation

Internal Cross-Validation

The trained model produced a cross validation correlation value of 0.899. This is a k-folds internal cross validation within the gbm.step function, which fits the model iteratively to each k-1 equally sized subset of the data and then tests the model on the remaining folds.

External Cross-Validation

Cross-validation was performed using a leave-one-out process. A manual n-1 leave one out (LOO) model cross-validation was performed, iteratively dropping the data points for 5 randomly selected gauges in the dataset (Table 2).

Table 2. Results of LOO cross-validation. PBIAS: percent bias; values closer to zero indicate less bias in the model. RMSE: root-mean square error; lower values indicate better precision in the model. RSR: rank sum ratio; lower values indicate better precision in the model. NSE: Nash-Sutcliffe Efficiency; higher values indicate more accurate and precise predictions.

Gauge ID	*PBIAS*	*RMSE*	*RSR*	*NSE*
11063500	259.000	32.010	9.360	-86.872
11063000	-22.100	3.944	1.002	-0.054
10259200	-5.900	4.932	0.656	0.568
10263500	-78.200	28.084	0.867	0.247
11153900	-82.100	82.035	1.007	-0.064

Prediction Validation

Reference predictions were validated by comparing the predicted values against 1) NWIS flow data, 2) SCCWRP provided logger data, and 3) USFS flow data for the region.

- USGS National Water Information System (NWIS) Flow Data – observed flow at 49 gauge locations. Mean monthly flow (cfs) for each month/year of available data within target period.
- SCCWRP Provided Flow Data – observed flow at 45 locations
- USFS Flow Data – observed flow at 8 locations

Observation (gauge) locations have varying degrees of anthropogenic influence. Within the validation data, gauge locations were classified as having minimal, moderate, or maximum anthropogenic influence and statistics were run on each level of anthropogenic influence as well as for the entire gauge/logger dataset (all levels of anthropogenic influence) for each source of data (Table 3).

Table 3. Results of validation for each of the three validation datasets. PBIAS: percent bias; values closer to zero indicate less bias in the model. RMSE: root-mean square error; lower values indicate better precision in the model. RSR: rank sum ratio; lower values indicate better precision in the model. NSE: Nash-Sutcliffe Efficiency; higher values indicate more accurate and precise predictions.

All Observation Locations				
Source	**PBIAS**	**RMSE**	**RSR**	**NSE**
NWIS	8.546	17224.322	1.387	-0.925
SCCWRP	-130.435	132.021	1.522	-1.316
USFS	-328.274	257.707	0.897	0.195
Minimal Anthropogenic Influence				
Source	**PBIAS**	**RMSE**	**RSR**	**NSE**
NWIS	-481.867	3011.423	6.072	-35.865
SCCWRP	-427.571	93.579	3.684	-12.573
USFS	-419.758	121.885	0.896	0.197
Moderate Anthropogenic Influence				
Source	**PBIAS**	**RMSE**	**RSR**	**NSE**
NWIS	-649.136	1515.727	3.610	-12.029
SCCWRP	-118.867	62.576	1.200	-0.439
USFS	-1240.678	143.629	0.972	0.056
Maximum Anthropogenic Influence				
Source	**PBIAS**	**RMSE**	**RSR**	**NSE**
NWIS	24.318	16891.157	1.362	-0.856
SCCWRP	-62.365	68.969	1.114	-0.242
USFS	-185.620	175.864	0.848	0.281

Additionally, using the NWIS flow data, predicted and observed values were averaged across all gauges by month in order to observe general trends when comparing predictions to observed values (Table 4, Figure 4). Overall, the model generally over-predicts for February, March, and April and under-predicts for all other months of the year.

Table 4. Comparison of predicted and observed values by month.

Month	*Predicted*	*Observed*	*% Change*
Jan	66.1	70.1	-6%
Feb	109.9	99.1	11%
Mar	103.9	76.9	35%
Apr	48.3	40.7	19%
May	17.7	32.5	-46%
Jun	8.2	20.8	-61%
July	7.2	16.3	-56%
Aug	7.1	14.6	-52%
Sept	5.4	13.8	-61%
Oct	7.5	19.6	-62%
Nov	9.0	22.0	-59%
Dec	25.6	39.0	-34%

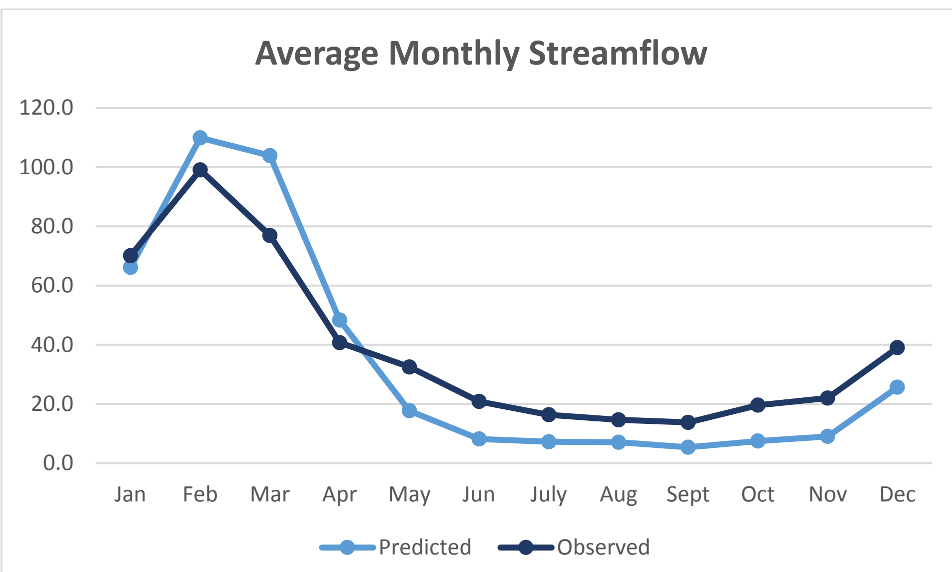


Figure 4. Predicted and observed values by month (units in cfs).

Although the model generally under-predicts for most months, it has over-predicted for approximately 75% of the total observations. And after removing observations that occur in February, March, and April (the months showing general over-predictions), the model has over-predicted for roughly 56% of the observations.

Classified Validation Comparisons

To provide additional validation, observed monthly mean flows were classified into categories and compared to similarly classified predicted data. Specifically, NWIS gauge observations and predicted flows were each classified as “dry” (less than 2 cfs), “intermediate” (2 to 10 cfs) or “wet” (>10 cfs), based on the observed mean monthly flow (one classification for each month). A prediction that matched observed data was given 1 point, and a prediction that was off by half (e.g., prediction of wet and an observation of intermediate) was given 0.5 points. The average score across all gauges was 0.66. Table 5 shows example scoring for three validation gauges.

Table 5. Cross validation of three example gauges

	Gauge 11060400			Gauge 11054000			Gauge 11048200		
	Observed (NWIS)	Predicted (Model)	Score	Observed (NWIS)	Predicted (Model)	Score	Observed (NWIS)	Predicted (Model)	Score
Jan	Wet	Wet	1	Int	Wet	0.5	Dry	Wet	0
Feb	Wet	Wet	1	Int	Wet	0.5	Dry	Wet	0
Mar	Wet	Wet	1	Wet	Wet	1	Dry	Wet	0
Apr	Wet	Wet	1	Wet	Wet	1	Dry	Wet	0
May	Int	Wet	0.5	Wet	Wet	1	Dry	Int	0.5
Jun	Int	Int	1	Wet	Int	0.5	Dry	Int	0.5
Jul	Int	Int	1	Int	Int	1	Dry	Int	0.5
Aug	Int	Int	1	Int	Int	1	Dry	Int	0.5
Sep	Int	Int	1	Int	Int	1	Dry	Int	0.5
Oct	Int	Int	1	Int	Int	1	Dry	Int	0.5
Nov	Int	Int	1	Int	Wet	0.5	Dry	Int	0.5
Dec	Int	Wet	0.5	Int	Wet	0.5	Dry	Wet	0
Average Score			*0.92*			*0.79*			*0.29*

Average scores for each gauge were joined to a geospatial point layer and the interpolation method inverse-distance-weighted (IDW) was applied to generally identify regions within the watershed where the model performed well under each of the conditions modeled (wet, normal, dry). This process was used to generate maps that show model performance in a spatially explicit fashion (Figure 5).

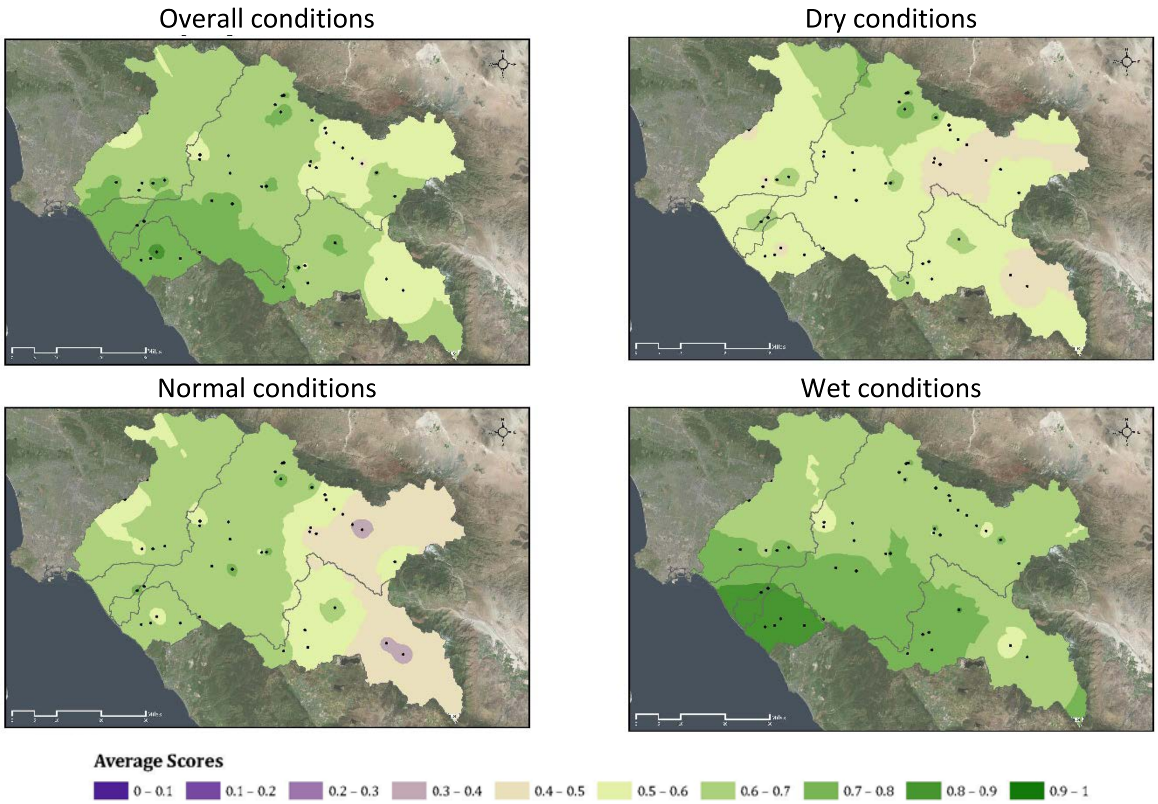


Figure 5: Maps of model performance under different climate conditions, as estimated by inverse-distance weighting. Darker (greener) colors indicate better performance.

3.9 Reference Model Testing

Reference predictions were generated twice due to the level of over-prediction seen in the initial predictions. Several methods were explored to reduce this bias, but only one (#1 on the list below) was found to be helpful:

1. Optimal number of regression trees
   In order to identify if the model was over fitting to the gauge data during model training, the optimal number of regression trees were identified and included during the predicting process. The optimal number of boosting iterations or trees for the training model (n =4896) was estimated using the gbm.perf function. The relative influence of each variable in the model, an assessment of the squared model improvement provided by splitting a tree by a given variable averaged across all modeled trees, was evaluated before further prediction. The results of this testing generally produced slightly drier predictions and the optimal number of regression trees was included in the script used to generate the final reference predictions.

These methods did not improve bias and were ultimately not adopted.

2. Iterative addition of variables
   In comparing the reference model for RWQCB 8 to that of RWQCB 9, it was noticed that the number of variables used for each of the models differ. During the variable selection process for RWQCB 8, 15 variables were selected. Whereas, during the variable selection process for RWQCB 9, 8 variables were selected. In order to determine if the model was not responding well to the increased number of variables used to train RWQCB 8, an iterative addition of variables was performed, starting from 8 and working up until the top 12 variables were included. During each iteration, the model was trained and values were predicted to identify if the model would predict more accurately. Overall, outputs of this testing resulted in wetter predictions than expected predictions with decreasing numbers of included variables.

3. Removed *aspect eastness* and *topographic wetness index* variables
   Aspect eastness and topographic wetness index variables were created by CSUN. The values of these variables were not as close to the data values that were used to train the model (Gages II dataset) as would have been preferred. In order to determine if removing one, or both, of the variables would improve the predictive power of the model, testing was performed. Three iterations of testing were performed, two iterations where each of the variables were removed independently and a third iteration where both variables were removed together. The results of testing are as follows:

   - Of the three tests performed, removing aspect eastness produced the driest output
   - Overall geographic trends were the same
   - Not significant enough to re-run predictions for entire model

4. Leave-one-out testing
   To identify if any specific gauge was contributing to inaccurate predictions produced by the model, a manual n-1 leave one out (LOO) model was performed, iteratively dropping data points for 30 of the gauges in the dataset. The results of this testing are as follows:

   - Majority of the predictions were wetter than original reference model
   - Some predictions showed minimal change
   - Not significant enough to re-run predictions for entire model

5. Removal of potentially problematic gauges
   Gauges producing questionable error values (PBIAS, RMSE, etc.) and those with anthropogenic influencers upstream were removed from the model on separate iterations to identify if the gauges were affecting predictions. The results of this testing are as follows:

   - Wetter predictions
   - Not significant enough to re-run predictions for entire model

3.10 Prediction Outputs

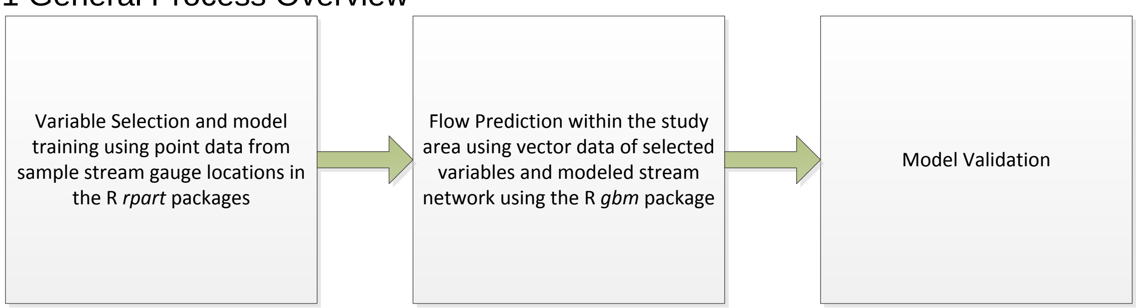
Prediction outputs of the model were converted to two different geospatial data formats. First, prediction data was converted to $30m^2$ raster datasets, with predictions for each month/condition (wet, normal, dry) contained within separate raster layers. Additionally, outputs have also been joined to NHDPlus flowlines using the "COMID" field as the primary key for the join. Raster prediction values for each month/condition were aggregated to generate the mean prediction for each "COMID" stretch within the NHDPlus flowline layer. In addition to the mean, the max, min, and standard deviation for each of the groups of prediction values aggregated to calculate the mean are included for each "COMID" stretch. The final product is one flowline layer with a separate field for the following:

- Predictions – each month/condition (e.g., normal January) in separate fields
- Max – max value used to aggregate prediction value
- Min – min value used to aggregate prediction value
- Standard deviation – standard deviation of the values used to aggregate prediction value

4. Anthropogenic Model Methods

4.1 Part I: Anthropogenic Model Pilot

4.1.1 General Process Overview



4.1.2 Gauge Selection P0rocess

Forty-nine stream gauges from within the Santa Ana watershed that were active for at least one full month within the target period (1981-2010) were selected to train the anthropogenic model; this span of years differs from the reference model (i.e., 1981-2012) because complete flow records were not available at certain sites. All stream gauges that meet these qualifications were selected. This set included the 4 reference gauges used to model historic flows, mentioned above.

4.1.3 Included Stream Features

Streams included in the anthropogenic modeling were selected using the same methods used to select reference streams features (section 2.3). However, since the variable data used was pre-processed and provided tabularly by COMIDs, using raster stream segments was not necessary (explanation of variables and source of variables is presented in Tables 1 and 5).

4.1.4 Flow Metrics

Flow metrics for this model are defined as the probability that anthropogenic flow would be inflated or diminished from reference conditions. In order to predict using these classifications, training data was classified into “inflated,” “diminished” and “unaltered” categories by dividing reference predicted flow (RP) into observed flow (O) (O/RP) for each flow observation at each gauge location and then using the following parameters to classify the data into the three descriptive categories (Eng et al. 2012):

- Diminished – O/RP < 90%
- Inflated – O/RP > 90%
- Unaltered – O/RP = 90%

The cutoff for flow being “inflated” or “diminished” occurs at 90% instead of 100% to account for a small percentage of the over-prediction that is present within the reference model outputs. This is consistent with the methods used by Eng et al. (2012). It should be noted that no flow record was classified as being “unaltered,” therefore models predict the probability that stream flow would be inflated or diminished from reference conditions.

The resolution of the variables selected for the anthropogenic model is the extent of NHD COMIDs. In order to provide consistency between the dependent (flow comparisons) and independent (anthropogenic) variables used, reference prediction values aggregated by COMID were used as reference flow (RP) values within the classification calculations.

4.1.5 Variable Selection Process

Variables for the anthropogenic models were hand-selected using variables included in Eng et al.’s (2012) anthropogenic model as a guide as well as expert feedback from Drs. Eric Stein and Raphael Mazor. Fifteen variables were hand-selected from the Environmental Protection Agency’s (EPA) StreamCat dataset and included in the variable importance process (Environmental Protection Agency n.d.) (Table 6). Variables assigned low values across the models were removed and not included in model training. Additionally, 7 pairs of similar variables were included in the variable importance process. Of these variables, those receiving an overall (across models) lower value of the pair were dropped and not included in model training.

Table 6. List of hand-selected variables included in the variable selection process for the anthropogenic model. Those with an “x” in the “Included in Model Training” field are the final variables selected and included in model training.

Variables	***Description***	***Included in Model Training***
PctAg2006Slp20Ws	Percent of the upstream watershed classified as agriculture (NLCD classes 81 and 82) occurring on slopes greater than or equal to 20%	x
PctAg2006Slp10Ws	Percent of the upstream watershed classified as agriculture (NLCD classes 81 and 82) occurring on slopes greater than or equal to 10%	
DamDensWs	Density of georeferenced dams within the upstream watershed	x

DamNIDStorWs	Volume of all reservoirs per unit area of the upstream watershed	x
DamNrmStorWs	Volume all reservoirs (NORM_STORA in NID) per unit area of the upstream watershed	
PctImp2006Ws	Mean of imp2006 values within the upstream watershed	x
PctImp2006WsRp100	Mean of imp2006 values within the upstream watershed within a 100-m buffer of the NHD stream lines	
RdDensWs	Mean of all rddens values within the upstream watershed rddens	x
RunoffWs	Mean of all runoff values within the upstream watershed	x
NPDESDensWs	Density of NPDES sites within the upstream watershed	x
NPDESDensWsRp100	Density of georeferenced NPDES sites within the upstream watershed within a 100-m buffer of the NHD stream lines	
SuperfundDensWs	Density of georeferenced Superfund sites within the upstream watershed	
SuperfundDensWsRp100	Density of georeferenced Superfund sites within the upstream watershedwithin a 100-m buffer of the NHD stream lines	
TRIDensWs	Density of georeferenced Toxic Release Inventory sites within the upstream watershed	
TRIDensWsRp100	Density of georeferenced Toxic Release Inventory sites within the upstream watershed within a 100-m buffer (of the NHD stream lines	

4.1.6 Model Training and Predictions

The anthropogenic models employed the *train* function in the *caret* package of R to evaluate, using resampling, the effect of model tuning parameters on performance, to choose the "optimal" model across these parameters, and to estimate the model's performance from the specified training data sets derived from anthropogenic gauges. A two-class (binary) model, classifying streams as either diminished or inflated in flow, was chosen given the scale of the training data that was readily available within the time frame allowed by this pilot project. Finer scale training data, requiring greater processing times, is necessary in our opinion to provide the level of accuracy needed to predict specific flow values with any level of confidence. Therefore, the outputs from the anthropogenic models provide a coarser resolution of flow predictions (i.e., probability of inflated or diminished flow), compared to the reference models (i.e., mean monthly flow).

A two-class gradient boosted model (gbm) was fit to the training data using 10-fold repeated internal cross validation in order to predict inflated versus diminished stream flow probabilities. Model performance was measured internally using area under the ROC curve metrics, sensitivity and specificity. This model function is designed to pick the tuning parameters associated with the best overall results. Specifically, the ROC parameter provided the cut off point for the binary prediction with the most accuracy. The relative influence of each variable was also measured to determine the reduction in the sum of squares error of the model assigned to each variable.

4.1.7 Model Validation

Internal Cross-Validation

A k-folds internal cross validation within the gbm.step function, which fits the model iteratively to each k-1 equally sized subset of the data and then tests the model on the remaining folds was performed 10 times to ensure model validity.

Prediction Validation

Anthropogenic predictions were validated by comparing the predicted values against, NWIS flow data, SCCWRP provided logger data, and USFS flow data for the region.

- USGS NWIS Flow Data – observed flow at 49 gauge locations. Mean monthly flow for each month/year of available data within target period. Data averaged by month/condition per gauge location.
- SCCWRP Provided Flow Data – observed flow at 45 locations
- USFS Flow Data – observed flow at 8 locations

In order to validate the accuracy of the predictions, observed flow was compared against the reference prediction at each location. If observed flow was less than predicted reference flow the record was classified for validation as being "diminished", whereas if the observed flow was greater than predicted reference flow it was classified as being "inflated." Next, anthropogenic model predictions were classified as being "inflated" or "diminished" based on which of the prediction fields had the highest probability. Then, the observed vs. predicted classifications were compared against the anthropogenic model prediction classifications to determine if the model generally predicted accurately. Using this method, an average of correct predictions was calculated using each of the three validation datasets (Table 7).

Table 7. Results of anthropogenic model validation.

Validation Dataset	% Correct Predictions	Number of Observations
NWIS	73%	1643
SCCWRP	87%	94
USFS	97%	80

4.1.8 Prediction Outputs

Prediction outputs for the anthropogenic model were joined to the NHDPlus flowlines. The final product is one flowline layer with a separate field with probability predictions for diminished and inflated flow for each month/condition (e.g., normal January).

4.2 Part II: Regional Comparison of Variable Importance

4.2.1 Overview of Task

The objective of this task was to identify important anthropogenic variables within both the regional board 8 and 9 watersheds. This information is important in determining if developing separate models for each region is necessary or if the modeling could be combined regionally.

4.2.2 Gauge Selection Process

Forty-five stream gauges from within RWQCB 8 and 33 stream gauges within RWQCB 9 that were active for at least one full month within the target period (1981-2010) were selected to use for the variable importance process. All stream gauges that meet the listed qualifications were selected.

4.2.3 Flow Metrics

Two versions of flow metrics were used during the variable importance process. One round of variable importance processing consisted of using mean monthly flow (cfs) for each month/condition, while another used the anthropogenic classification methods (diminished vs. inflated) outlined in section 4.1.4.

4.2.4 Variable Importance Process

Nine hand-selected variables from the USGS Gages II (Falcone 2011) dataset were selected for the variable importance process (Table 8). Since predictions for RWQCB 9 were only performed for March, May, and September, variable importance has only been performed for these three months.

Table 8. Hand-selected variables used in the variable importance process.

Variable	*Description*
ROADS_KM_SQ_KM	Road density, km of roads per watershed sq km, from Census 2000 TIGER roads
IMPNLCD06	Watershed percent impervious surfaces from 30-m resolution NLCD06 data
NPDES_MAJ_DENS	Density of NPDES (National Pollutant Discharge Elimination System) "major" point locations in watershed; number per 100 km sq. Major locations are defined by an EPA-assigned major flag. From download of NPDES national database summer 2006.
PCT_IRRIG_AG	Percent of watershed in irrigated agriculture, from USGS 2002 250-m MODIS data
DDENS_2009	Dam density; number per 100 km sq
STOR_NID_2009	Dam storage in watershed ("NID_STORAGE"); megaliters total storage per sq km (1 megaliters = 1,000,000 liters = 1,000 cubic meters)
STOR_NOR_2009	Dam storage in watershed ("NORMAL_STORAGE"); megaliters total storage per sq km (1 megaliters = 1,000,000 liters = 1,000 cubic meters)
MAJ_NDAMS_2009	Number of "major" dams in watershed. Major dams defined as being >= 50 feet in height (15m) or having storage >= 5,000 acre feet (National Atlas definition)
MAJ_DDENS_2009	Major dam density; number per 100 km sq

4.2.5 Outputs

Two rounds of variable importance processing were run, one using mean monthly flow and another using the binary classification methods. Results from each round are shown in Table 9.

Table 9. Variable importance for predicting mean monthly flows or binary classifications (e.g., inflated, diminished) for the anthropogenic model. Dashes indicate that the variable was not included in the model.

			Wet						Normal						Dry					
	Overall		March		May		Sep		March		May		Sep		March		May		Sep	
Binary classification	RB8	RB9	RB8	RB9	RB8	RB9	RB8	RB9	RB8	RB9	RB8	RB9	RB8	RB9	RB8	RB9	RB8	RB9	RB8	RB9
ROADS_KM_SQ_KM	19	21	16	23	14	27	20	12	18	16	17	10	19	12	18	24	18	15	18	13
IMPNLCD06	15	21	11	25	15	21	15	12	12	18	16	12	18	12	9	19	13	10	12	12
NPDES_MAJ_DENS	13	7	10	4	9	4	11	7	12	-	12	6	8	5	15	4	15	10	15	5
PCT_IRRIG_AG	9	10	4	13	5	12	8	9	9	12	10	8	10	5	10	14	9	12	9	6
DDENS_2009	13	11	10	5	11	9	13	10	13	9	15	11	13	8	9	8	13	11	10	9
STOR_NID_2009	6	13	11	9	10	10	10	16	7	14	6	18	5	17	11	9	6	15	8	17
STOR_NOR_2009	6	10	12	8	12	10	7	15	8	14	6	17	7	17	10	9	7	16	9	17
MAJ_NDAMS_2009	6	3	17	3	18	4	5	9	10	8	5	6	6	13	15	5	7	3	7	11
MAJ_DDENS_2009	12	6	8	11	7	4	11	10	10	10	14	12	14	11	3	7	12	8	11	10
Mean monthly flow																				
ROADS_KM_SQ_KM	9	11	6	9	13	5	8	7	-	5	-	9	3	12	2	9	-	5	-	15
IMPNLCD06	1	8	3	11	3	5	6	6	1	4	1	6	3	8	2	9	-	2	-	9
NPDES_MAJ_DENS	16	8	15	4	21	3	9	9	1	3	1	10	4	11	3	16	2	9	2	7
PCT_IRRIG_AG	17	8	14	8	16	4	45	8	65	3	62	6	60	2	53	7	57	2	55	6
DDENS_2009	1	6	2	5	3	4	7	8	3	3	7	8	6	7	5	7	5	5	6	7
STOR_NID_2009	10	29	6	25	9	66	9	8	3	8	6	13	6	40	5	41	6	20	7	41
STOR_NOR_2009	11	2	4	25	12	1	3	37	-	52	-	36	-	-	1	1	1	43	1	-
MAJ_NDAMS_2009	33	16	47	7	21	8	12	14	22	21	15	10	12	15	25	9	23	9	22	8
MAJ_DDENS_2009	1	12	2	7	3	3	2	2	3	1	7	2	5	6	5	1	5	4	7	7

5. REFERENCE & ANTHROPOGENIC MODELING COMPARISON

This section highlights the differences between the reference and anthropogenic models to facilitate a better understanding of the modeling processes used (Figure 6).

The main difference between the modeling processes used is that reference modeling was performed using one model and anthropogenic modeling was performed using a separate model for each month/condition being modeled (36 models). This is due to the methods used to predict to months and year conditions (wet, normal, dry) within the reference and anthropogenic models. When developing the reference model, the process for predicting to each month/condition was built into the independent climate variables as climate variables were tailored to the month/condition being modeled. These tailored climate variables were included in the dataset used to train the model as well as the dataset used to generate predictions. For model training, each record included information on the month and year that flow values were captured. Using this information, specific climate variable values associated with the month and year of the flow record were used. This trained the model to the different climate conditions that occurred within each of the months/conditions being modeled. When it came to predicting, landscape variables remained consistent across the 36 input datasets, while the climate variables were tailored to the month/condition being modeled. For example, if predicting for a normal January, climate variables only consisted of observations that occurred in January under normal climate conditions.

Since the anthropogenic model does not contain variables with specific information associated with the months or conditions (wet, normal, dry) being modeled, the flow dates (months and years) were separated into 36 groupings each only consisting of flow observations occurring during a given month/condition. Each group of specific month/condition data was used to train a separate anthropogenic model. Wet, normal, and dry conditions were defined using the same condition years used to classify the climate data within the reference model. When predicting, one input dataset with anthropogenic variables was used to generate predictions for each model.

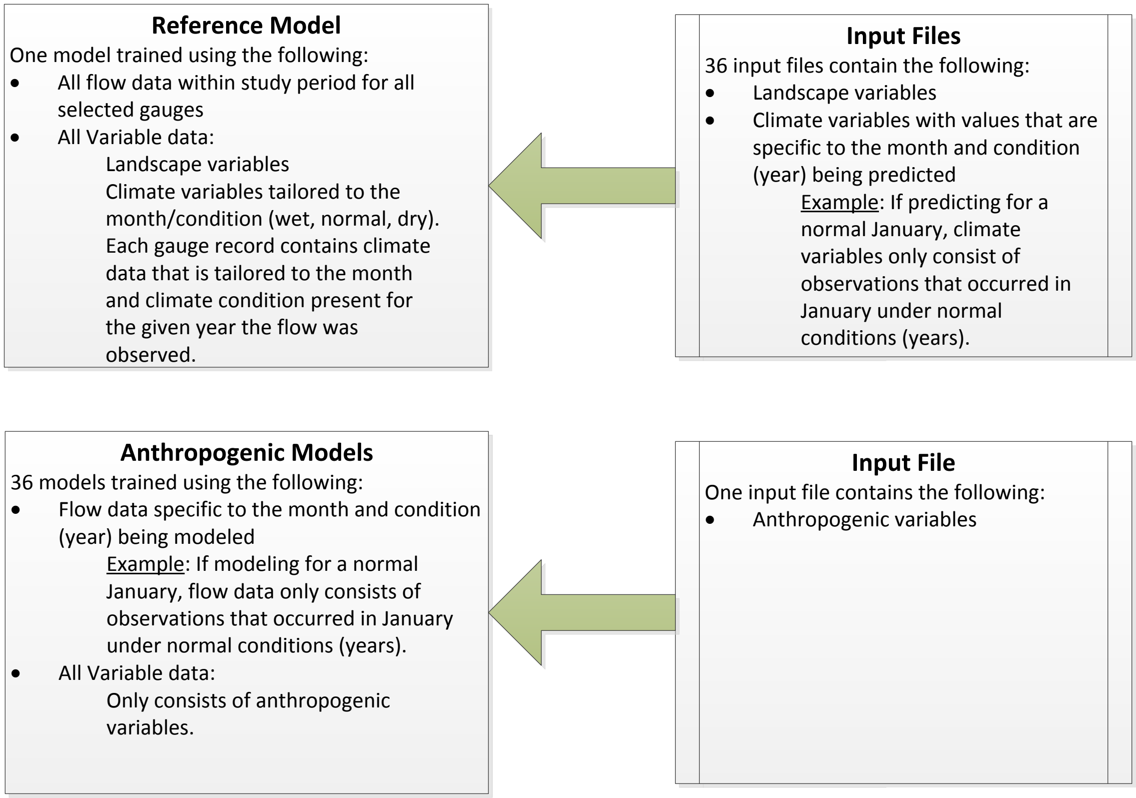


Figure 6. Diagrams explaining differences between reference and anthropogenic models and input prediction files.

6. SUMMARY OF FLOW SIMULATIONS UNDER REFERENCE AND ANTHROPOGENIC CONDITIONS

Stream flow estimates from the two geodatabases were used to assess hydrologic conditions in the Santa Ana region. The purpose of this analysis was to demonstrate where and when stream flow conditions are expected to change in each watershed. Modelled flow estimates from 3447 stream reaches in five catchments were summarized to quantify stream miles under different hydrologic conditions. Flow estimates were based on reference scenarios under historical, non-impacted land use conditions. Monthly flow was estimated for dry, normal, and wet years. Likelihood of flow conditions inflating, diminishing, or remaining stable under present-day land cover was also summarized for each watershed.

Historic flows were estimated to be highest in the high elevations of the San Gabriel, San Bernardino, and San Jacinto mountains, while the lowest flows were in the inland valleys (Figure 7). Flow estimates for the Upper Santa Ana were generally higher than those for the Lower Santa Ana. Flow estimates also increased as expected under different climate conditions such that greater flow was estimated during wet years.

Estimates were highest during winter to early spring (January through April) when estimated flows > 100 cfs were more common, across all watersheds (Figure 8, Table 10). Similarly, low flows < 1 cfs were more common during the summer and fall. Unsurprisingly, flows were higher in wet conditions than dry, although this impact was more obvious in some watersheds (e.g., Upper Santa Ana) than others (e.g., Lower Santa Ana). Late summer flows over 10 cfs were limited to small portions of the region—and nearly eliminated from certain watersheds (e.g., San Jacinto, Lower Santa Ana), even in wet years.

Diminishing flow was the most common prediction under anthropogenic conditions, although some exceptions were observed (Figure 9, Table 11). Stream reaches were more likely to remain stable during the winter, particularly in December. Flow conditions were also more likely to be stable during wet years. Interestingly, stream conditions in January under normal precipitation were most likely to be inflated, whereas conditions were expected to be stable during wet years. Patterns between catchments were generally consistent.

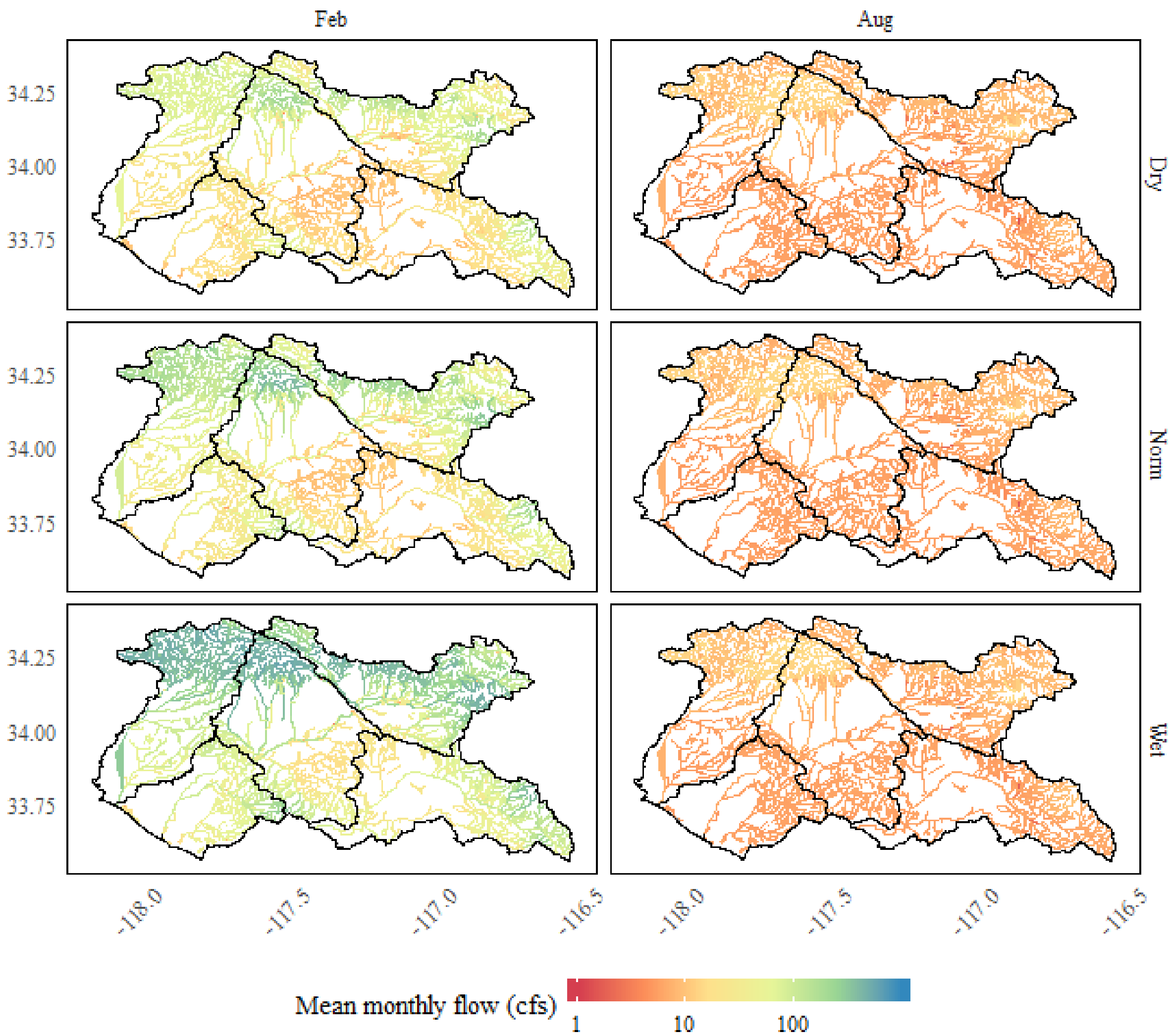


Figure 7. Estimated flow under historic (reference) conditions.

Figure 8. Percent of stream length for the estimated discharge (< 1 cfs, 1 - 10 cfs, 10 - 100 cfs, > 100 cfs) under reference conditions. Discharges were also estimated for different climate scenarios for years that were dry, normal, or wet. SGB: San Gabriel; LSA: Lower Santa Ana; MSA: Middle Santa Ana; USA: Upper Santa Ana; and SJC: San Jacinto.

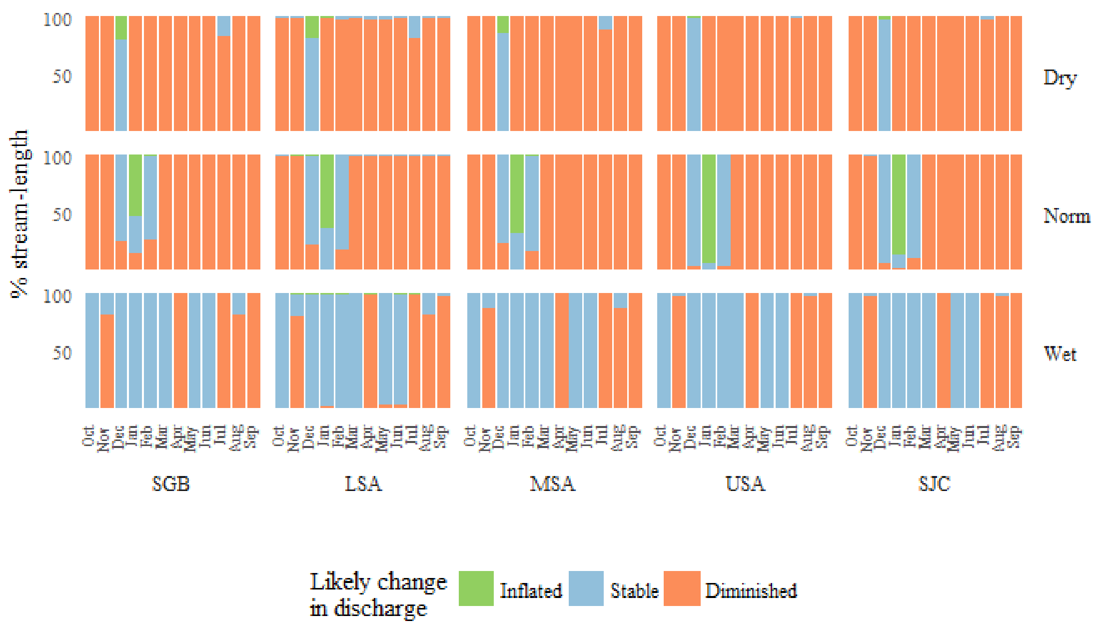


Figure 9. Percent of stream length for the estimated likelihood of a change in discharge as inflating, remaining stable, or diminishing under anthropogenic conditions. Likelihoods were estimated for different climate scenarios for years that were dry, normal, or wet. SGB: San Gabriel; LSA: Lower Santa Ana; MSA: Middle Santa Ana; USA: Upper Santa Ana; and SJC: San Jacinto.

Table 10. Stream-length (km) in flow classes in each watershed, by month and climate condition. Flows are in cfs. Dashes indicate zero values.

	Dry				Normal				Wet			
Watershed	< 1	1 - 10	10 - 100	> 100	< 1	1 - 10	10 - 100	> 100	< 1	1 - 10	10 - 100	> 100
San Gabriel												
Oct	--	8.07	3.79	--	--	8.12	3.73	--	--	6.45	5.41	--
Nov	--	5.18	6.68	--	--	4.18	7.68	--	--	3.83	8.03	--
Dec	--	2.97	8.89	--	--	2.09	9.75	0.02	--	0.62	10.25	0.99
Jan	--	1.16	10.70	--	--	0.01	10.98	0.86	--	0.01	3.67	8.19
Feb	--	0.01	11.44	0.40	--	--	5.26	6.59	--	--	2.88	8.98
Mar	--	0.77	11.09	--	--	0.01	10.54	1.31	--	--	0.58	11.27
Apr	--	1.72	10.14	--	--	0.15	11.52	0.19	--	--	3.86	7.99
May	--	3.33	8.53	--	--	3.30	8.55	--	--	0.15	11.29	0.42
Jun	--	5.83	6.03	--	--	5.71	6.14	--	--	4.82	7.04	--
Jul	--	8.41	3.45	--	--	8.30	3.55	--	--	7.35	4.50	--
Aug	--	8.55	3.31	--	--	8.74	3.12	--	--	8.25	3.61	--
Sep	--	8.33	3.52	--	--	7.79	4.06	--	--	8.35	3.51	--
Lower Santa Ana												
Oct	0.01	7.22	--	--	0.01	7.22	--	--	0.01	7.22	--	--
Nov	0.01	7.22	--	--	0.01	7.22	--	--	0.01	7.22	--	--
Dec	--	7.10	0.14	--	--	4.58	2.65	--	--	2.40	4.84	--
Jan	--	3.77	3.47	--	--	0.18	7.05	--	--	0.15	6.52	0.57
Feb	--	0.23	7.01	--	--	0.07	6.98	0.18	--	0.05	6.17	1.01
Mar	--	3.98	3.26	--	--	0.24	6.99	--	--	0.01	2.98	4.25
Apr	--	5.50	1.74	--	--	1.00	6.24	--	--	0.06	6.95	0.23
May	--	7.21	0.03	--	--	7.12	0.11	--	--	0.81	6.42	--
Jun	0.01	7.22	--	--	0.01	7.22	--	--	--	7.24	--	--
Jul	0.01	7.22	--	--	0.01	7.22	--	--	0.01	7.22	--	--
Aug	0.01	7.22	--	--	0.01	7.22	--	--	0.01	7.22	--	--
Sep	0.01	7.22	--	--	0.01	7.22	--	--	0.01	7.22	--	--

Middle Santa Ana												
Oct	--	10.30	2.96	--	--	10.30	2.96	--	--	9.91	3.34	--
Nov	--	10.18	3.08	--	--	9.18	4.08	--	--	8.92	4.34	--
Dec	--	8.05	5.21	--	--	7.05	5.15	1.06	--	5.38	5.16	2.72
Jan	--	6.31	6.55	0.40	--	3.41	7.36	2.49	--	2.45	6.11	4.70
Feb	--	2.06	8.94	2.26	--	0.76	8.83	3.67	0.01	0.08	7.72	5.46
Mar	--	7.06	5.91	0.30	--	2.66	8.07	2.53	0.01	0.03	6.01	7.21
Apr	--	7.52	5.65	0.09	--	5.04	7.09	1.12	0.01	0.10	9.10	4.05
May	--	8.49	4.77	--	--	8.51	4.74	--	--	4.79	7.15	1.32
Jun	--	10.23	3.03	--	--	10.23	3.03	--	--	10.01	3.25	--
Jul	--	10.33	2.93	--	--	10.33	2.93	--	--	10.30	2.96	--
Aug	--	10.33	2.93	--	--	10.33	2.93	--	--	10.33	2.93	--
Sep	--	10.33	2.93	--	--	10.22	3.04	--	--	10.33	2.93	--
Upper Santa Ana												
Oct	--	14.02	1.10	--	0.01	13.27	1.83	--	0.01	10.53	4.58	--
Nov	--	10.81	4.31	--	--	6.75	8.31	0.05	--	6.57	8.55	--
Dec	--	4.80	10.32	--	--	2.46	12.53	0.13	--	1.43	12.56	1.12
Jan	--	2.30	12.74	0.07	--	0.83	12.27	2.03	--	0.19	4.64	10.29
Feb	--	0.26	12.49	2.37	--	0.19	10.23	4.70	0.01	0.13	2.70	12.28
Mar	--	2.58	12.54	--	--	0.30	12.26	2.55	0.01	0.07	1.39	13.65
Apr	--	3.01	12.11	--	--	1.54	13.55	0.03	--	0.15	7.89	7.07
May	--	6.17	8.95	--	--	5.81	9.31	--	--	0.84	14.20	0.08
Jun	--	12.25	2.87	--	--	12.56	2.56	--	--	9.20	5.92	--
Jul	--	14.30	0.82	--	--	14.34	0.78	--	--	13.85	1.27	--
Aug	0.01	14.43	0.68	--	0.01	14.46	0.65	--	0.01	14.39	0.72	--
Sep	0.01	14.43	0.68	--	0.01	13.39	1.72	--	0.01	14.31	0.80	--
San Jacinto												
Oct	--	11.42	0.05	--	--	11.42	0.05	--	--	10.95	0.53	--
Nov	--	10.92	0.56	--	--	10.36	1.12	--	--	9.93	1.54	--
Dec	--	9.75	1.72	--	--	7.23	4.24	--	--	4.06	7.41	--
Jan	--	6.32	5.15	--	--	2.66	8.63	0.18	--	0.57	9.56	1.35

Feb	--	1.06	10.11	0.30	--	0.24	10.78	0.44	--	--	9.23	2.24
Mar	--	6.77	4.70	--	--	1.80	9.52	0.15	--	--	6.07	5.41
Apr	--	7.33	4.15	--	--	5.17	6.30	--	--	--	10.68	0.80
May	--	10.47	1.01	--	--	10.15	1.32	--	--	3.86	7.61	--
Jun	--	11.24	0.23	--	--	11.28	0.20	--	--	10.90	0.58	--
Jul	--	11.47	--	--	--	11.47	--	--	--	11.38	0.09	--
Aug	--	11.47	--	--	--	11.47	--	--	--	11.44	0.03	--
Sep	--	11.47	--	--	--	11.45	0.03	--	--	11.47	--	--

Table 11. Stream-length (km) in flow alteration class in each watershed, by month and climate condition. Inflated: Probability that flow is increased from historic conditions ≥ 0.9. Diminished: Probability that flow is decreased from historic conditions ≥ 0.9. Stable: Probability that flow has neither increased nor decreased from historic conditions ≥ 0.8. Dashes indicate zero values.

	Dry			Normal			Wet		
Watershed	Inflated	Stable	Diminished	Inflated	Stable	Diminished	Inflated	Stable	Diminished
San Gabriel									
Oct	--	--	11.9	--	--	11.9	--	11.9	--
Nov	--	--	11.9	--	--	11.9	--	2.1	9.7
Dec	2.3	9.6	--	--	8.8	3.0	--	11.9	--
Jan	--	--	11.9	6.3	3.7	1.8	--	11.9	--
Feb	--	--	11.9	0.1	8.7	3.1	--	11.9	--
Mar	--	--	11.9	--	--	11.9	--	11.9	--
Apr	--	--	11.9	--	--	11.9	--	--	11.9
May	--	--	11.9	--	--	11.9	--	11.9	--
Jun	--	--	11.9	--	--	11.9	--	11.8	--
Jul	--	2.1	9.8	--	--	11.9	--	--	11.9
Aug	--	--	11.9	--	--	11.9	--	2.1	9.7
Sep	--	--	11.9	--	--	11.9	--	--	11.9
Lower Santa Ana									
Oct	--	--	7.2	--	--	7.2	--	7.2	--
Nov	--	--	7.2	--	0.1	7.1	--	1.4	5.8
Dec	1.3	5.9	--	--	5.6	1.6	--	7.2	--
Jan	--	--	7.2	4.5	2.7	--	--	7.1	0.1
Feb	--	0.1	7.1	--	5.9	1.3	--	7.2	--
Mar	--	--	7.2	--	--	7.2	--	7.2	--
Apr	--	0.1	7.1	--	--	7.2	--	--	7.2
May	--	0.1	7.1	--	0.1	7.1	--	7.0	0.2

Jun	--	--	7.2	--	--	7.2	--	7.0	0.2
Jul	--	1.3	5.9	--	--	7.2	--	--	7.2
Aug	--	--	7.2	--	--	7.2	--	1.4	5.9
Sep	--	--	7.2	--	--	7.2	--	0.1	7.1
Middle Santa Ana									
Oct	--	--	13.3	--	--	13.3	--	13.3	--
Nov	--	--	13.3	--	--	13.3	--	1.5	11.7
Dec	1.9	11.4	--	--	10.1	3.1	--	13.3	--
Jan	--	--	13.3	8.9	4.2	0.1	--	13.3	--
Feb	--	--	13.3	0.1	11.0	2.2	--	13.3	--
Mar	--	--	13.3	--	--	13.3	--	13.3	--
Apr	--	--	13.3	--	--	13.3	--	--	13.3
May	--	--	13.3	--	--	13.3	--	13.3	--
Jun	--	--	13.3	--	--	13.3	--	13.2	0.1
Jul	--	1.6	11.7	--	--	13.3	--	--	13.3
Aug	--	--	13.3	--	--	13.3	--	1.6	11.7
Sep	--	--	13.3	--	--	13.3	--	--	13.3
Upper Santa Ana									
Oct	--	--	15.1	--	--	15.1	--	15.1	--
Nov	--	--	15.1	--	--	15.1	--	0.3	14.9
Dec	0.3	14.9	--	--	14.6	0.5	--	15.1	--
Jan	--	--	15.1	14.2	0.8	0.1	--	15.1	--
Feb	--	--	15.1	--	14.5	0.6	--	15.1	--
Mar	--	--	15.1	--	--	15.1	--	15.1	--
Apr	--	--	15.1	--	--	15.1	--	--	15.1
May	--	--	15.1	--	--	15.1	--	15.1	--
Jun	--	--	15.1	--	--	15.1	--	15.0	0.1

Jul	--	0.2	14.9	--	--	15.1	--	--	15.1
Aug	--	--	15.1	--	--	15.1	--	0.3	14.9
Sep	--	--	15.1	--	--	15.1	--	--	15.1
San Jacinto									
Oct	--	--	11.5	--	--	11.5	--	11.5	--
Nov	--	--	11.5	--	--	11.4	--	0.3	11.2
Dec	0.3	11.2	--	--	10.8	0.7	--	11.5	--
Jan	--	--	11.5	9.9	1.4	0.1	--	11.5	--
Feb	--	--	11.4	--	10.3	1.2	--	11.5	--
Mar	--	--	11.5	--	--	11.5	--	11.5	--
Apr	--	--	11.4	--	--	11.5	--	--	11.5
May	--	--	11.4	--	--	11.5	--	11.4	--
Jun	--	--	11.5	--	--	11.5	--	11.4	--
Jul	--	0.2	11.2	--	--	11.5	--	--	11.5
Aug	--	--	11.5	--	--	11.5	--	0.2	11.2
Sep	--	--	11.5	--	--	11.5	--	--	11.5

7. Using the data to support management decisions

Flow models may help determine causes of poor biological condition (Figure 10). The circled area in the left plot shows a cluster of bioassessment sites with low CSCI scores in the lower Santa Ana watershed. However, stable flow (green) is predicted on the mainstem of the Santa Ana River and inflated flow (blue) is predicted on the Santiago Creek tributary. Stressors from elevated flow could be further investigated as a potential cause of low CSCI scores in the Santiago Creek tributary, whereas flow stressors are less likely in the Santa Ana River. This information is helpful for identifying flow as a potential stressor of biological condition or if additional information is needed to characterize other stressors.

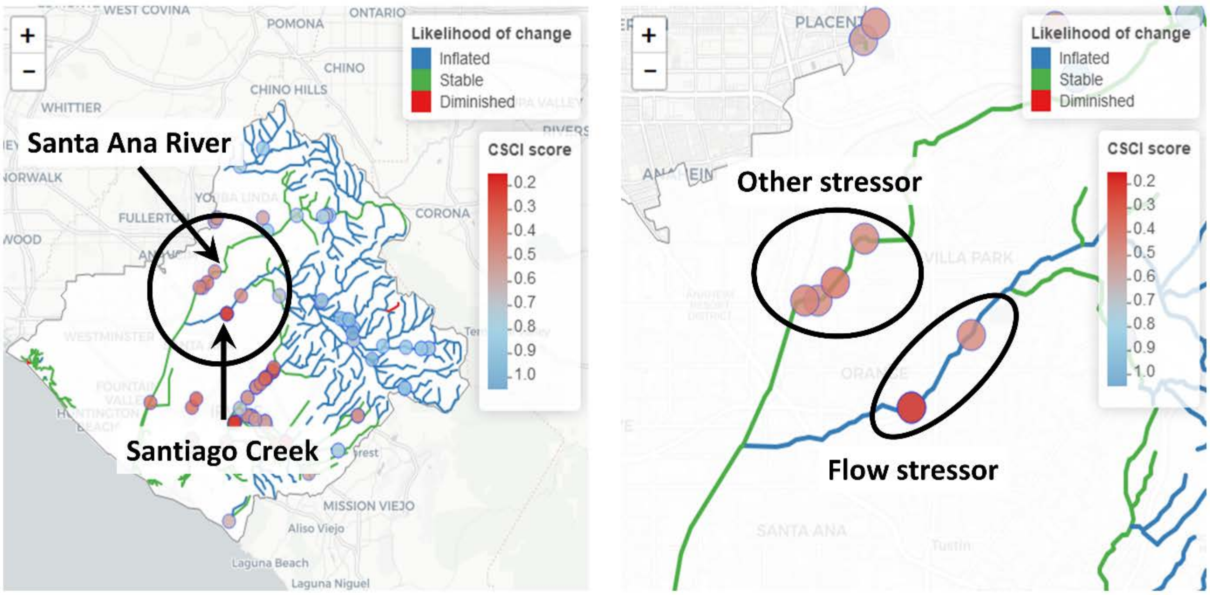


Figure 10. An example identifying stressors of poor biological condition from model output.

Models may also be used to prioritize locations for additional monitoring or habitat evaluation from potential effects of hydromodification (Figure 11). The estimated flows in January under normal climatic conditions for the Santa Ana region are shown. Reference flows increase from the lower to upper watersheds. Under anthropogenic conditions, stream reaches are estimated as having a mix of stable or inflated flows in most of the region. However, stream reaches in the upper watershed near the San Antonia area are projected to have diminished flows (red circle). These areas may have non-perennial streams under anthropogenic flows and normal climatic scenarios. An effective approach may prioritize stream monitoring in these areas that are most likely to change to non-perennial status.

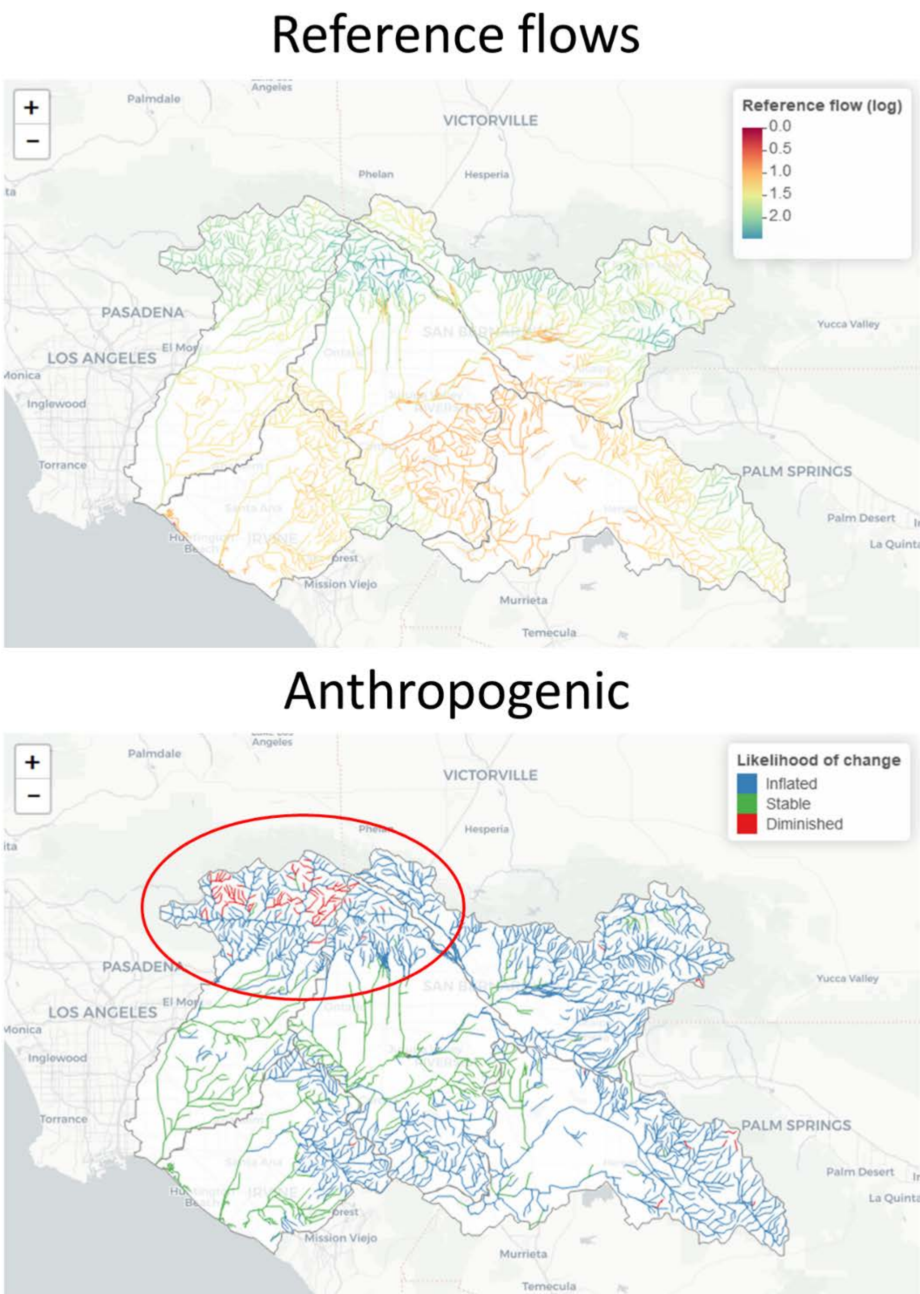


Figure 11. An example identifying streams for prioritizing monitoring efforts in the Santa Ana region.

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