## Enhancing Adaptive Management: The role of modeling to augment monitoring and management decisions

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## Abstract

Adaptive management is a widely used approach for supporting decision making in the face of uncertainty, but its success relies on the timely refinement of management strategies in response to ongoing monitoring. In this study, we demonstrate the role of modeling to inform implementation of an adaptive management plan for flow management in urbanized San Gabriel River, California, USA. We applied a combination of statistical modeling techniques to assess the impact of reduced discharge from water reclamation plants on riparian vegetation. Using stem water potential and canopy volume as indicators of plant stress, we examined their response to changes in discharge over a five-year monitoring period. Our results showed that stem water potential was more responsive based on environmental conditions than canopy volume, although no significant relationship was found between reduced discharge and overall plant stress. This lack of clear relationship is likely due to inherent variability within the system, including differences among species and their proximity to the flow, which may be obscuring the potential effects of flow reductions. By incorporating these findings into the adaptive management plan, we refined the monitoring strategy early on, optimizing resource reallocation and focusing on the most sensitive indicators of stress. Our study demonstrates the value of early implementation of modeling in adaptive management, allowing for more timely decision-making and improved management outcomes in flow-regulated systems.

## Introduction

Adaptive management (AM) is a commonly proposed tool to support decision making in the face of uncertain outcomes.  Adaptive management is an iterative process that involves exploring alternative ways to meet a range of management objectives, predicting the outcomes based on the current state of knowledge, implementing one or more of these alternatives, monitoring to learn about the impacts of the selected management actions, and then using the results to update knowledge and adjust management actions (Walters, 1997). Since its inception, AM has become increasingly necessary as resource management decisions have become more complex (considering multiple stressors) and because changing climate conditions increase non-stationarity in systems being managed. This is particularly true for aquatic ecosystems which are often subjected to multiple co-occurring stressors, are highly variable by nature, and rely on certain amounts of dynamism to maintain ecological health.

Unfortunately, few adaptive management programs have succeeded in realizing the general goals of reducing uncertainty by iteratively learning from prior outcomes while developing “hypotheses” to improve future management and monitoring. To achieve these goals, AM must be clearly aligned with management objectives and targets which need to be as specific as possible so that they can be both measured and evaluated while accounting for multiple possible outcomes (Capon et al. 2018). Targets must be periodically re-evaluated and adjusted to account for changing climatic conditions and lessons learned from early monitoring efforts. This can be particularly daunting for managers and scientists dealing with flow alteration as indicators often take years to respond to show measurable responses to flow interventions. This delay can complicate decisions on how to adapt interventions, increasing the risk and uncertainty associated with achieving desired environmental outcomes (Capon et al. 2018).

Prosser et al. (2021) note that differences between the theory of adaptive management and its actual practice arise because the lifetime of a decision includes the lead time it takes from deciding to act to when the decision is implemented, the operational time over which the implementation is active or over which benefits are reaped, and the consequence time over which the legacy of the decision continues. Successful AM programs have allowed for the time necessary to accumulate enough data to draw meaningful conclusions and identify factors whose adjustment can be expected to yield positive results. For example, the Columbia Estuary Ecosystem Restoration Program evolved over 12 years beginning with fundamental research and small-scale pilot implementation projects. Observations from the early phase projects informed development of a more mature adaptive management program that incorporated early lessons learned to inform more ambitious restoration and management activities (Littles et al. 2022). Similarly, the environmental flow management program from the Terzaghi Dam in British Columbia, Canada was established to support ecological functioning of the Lower Bridge River. After the initial four years of monitoring, the adaptive management program resulted in scaled back monitoring related to benthic health, which was determined to not be diagnostic of ecological responses to flow management and the program-initiated changes to sampling methods to reduce uncertainties that hindered interpretation of the data (Failing et al. 2013).

The complexity of natural systems requires many years of monitoring to develop data sets with sufficient power to test adaptive management hypotheses and thereby improve management.  This is particularly true in older management programs that may not have been designed specifically to accommodate AM. Moreover, to be successful, an AM process must follow a sound decision-making process and meaningfully and continuously engage external stakeholders and include a mechanism for dealing with different stakeholder values and risk tolerances over uncertain outcomes (Failing et al. 2013). However, the extended timeframes necessary to inform AM decisions are problematic because 1) regulatory and management agencies often require decisions to be made more quickly to meet regulatory timeframes, and 2) stakeholder composition changes over time creating lapses in institutional memory and continuity; this is particularly important because ongoing stakeholder coordination is crucial to successful adaptive management (Drury et al. 2011).

Modeling has the potential to contribute to successful AM by providing insight into relationships between management actions and ecological response earlier in the monitoring process (Irving et al, in review). Modeling provides a way to assess monitoring data during the first several years of program implementation by analyzing relationships between actions, environmental covariates, and response measures earlier in the monitoring trajectory and relate them to AM criteria. This can help managers understand where (and how) to focus on reducing uncertainty, and where to invest in enhanced monitoring (Runge et al., 2011). In addition, modeling can be used to help predict how management interventions may (or may not) affect ecological outcomes to inform hypothesis driven AM. Collectively, this allows for earlier decision making and supports process documentation that can create a legacy of the decision-making process for stakeholders.

Here we demonstrate the role of modeling to inform implementation of an adaptive management plan for flow management in the urbanized San Gabriel River, California, USA where modification of discharge of treated wastewater is desired to promote water reuse, without adversely affecting habitat and sensitive species reliant on the flows. This project provides important lessons learned for other AM programs that are considering modeling as a tool to support the decision-making process.

### Adaptive Management Plan Background

The 59-mile-long San Gabriel River (SGR) receives drainage from 689 square miles of eastern Los Angeles County, California. The headwaters of the SGR originate in the San Gabriel Mountains and are dominated by forested and scrub-shrub landscapes. The SGR is controlled by five dams, with three in the upper watershed and two in the urbanized lower watershed. The lower SGR is largely channelized with flows heavily managed through diversions, spreading grounds, and rubber dams. Five water reclamation plants (WRPs) operated by the Los Angeles County Sanitation Districts (hereafter referred to as the Districts) discharge tertiary‐treated disinfected wastewater effluent to the lower San Gabriel River, which is the predominant source of non-storm flow in the river. This study involves the discharge from Pomona (PO), San Jose Creek (SJC) and Whittier Narrows (WN) WRPs.

From 2018 to 2020 the Districts received authorization from the California Water Resources Control Board to reduce their discharge into the SGR to support water reuse projects in the region. Because the reduced discharge has the potential to adversely affect riparian habitat that has historically been occupied by the federally (U.S.Fish and Wildlife, 1986) and state (California Endangered Species Act) endangered Least Bell’s Vireo (*Vireo bellii pusillus;* LBV) downstream of the WRP discharge, the Districts were required to develop an Adaptive Management Plan (AMP) as part of their compliance with state and federal regulations.

The goal of the AMP is to ensure, through monitoring and adaptive management, that baseline riparian conditions (and health) are maintained over the lifetime of the reuse project (Wood, 2020). The AMP is to provide a method of monitoring site conditions, i.e., the monitoring plan, each year to evaluate habitat characteristics for the LBV and to assess whether there have been changes to habitat that would trigger consideration of changes to management activities such as increases in flow.

The AMP is overseen by an interagency Habitat Management Committee (HMC), who are responsible for reviewing monitoring data semiannually and determining if discharges are resulting in adverse effects on riparian habitat sufficient to trigger reduction of reuse, increases in flows and additional monitoring (Wood 2020). The HMC consisted of state and federal wildlife agencies (California Department of Fish and Wildlife, U.S. Fish and Wildlife Service), LA Water Keeper, U.S. Army Corp of Engineers, LA County Department of Public Works, Water Replenishment District, MSGB Watermaster, Heal the Bay, Council for Watershed Health, Sierra Club, and the State and Regional Water Boards, with the Districts being responsible for overseeing the implementation and ensuring compliance.

The objectives of the AMP are to ensure continuation of the pre-Project conditions (overall quality and quantity) of the habitat influenced by treatment plant discharges. To accomplish this, it is important to understand:

* Relationships between changes in WRP discharge and habitat quality
* Sensitivity of the selected stressors to changes in SGR river flow
* Relative influence of changes in WRP discharge vs. other stressor variables on habitat
* Intensity and duration of monitoring necessary to detect habitat changes associated with flow modifications

A close-up of a map

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Figure 1: Map of project area, with a) tree groups containing Vireo habitat and b) effluent discharge points, stream gage stations and monitoring wells.

## Methods

The AMP monitoring plan is focused on portions of the SGR and associated areas that may be affected by changes in the volume of water released from WRPs between the primary discharge point in San Jose Creek (a major tributary to the San Gabriel River) and the crossing of San Gabriel River Parkway over the San Gabriel River (approximately 3.17 miles downstream of the discharge). Additional monitoring occurs in the Zone 1 Ditch, the Whittier Narrows Cross Channel, and the area upstream of the confluence of San Jose Creek and the SGR. These areas have been separated into five (5) habitat groups (Group 1 to 5; G1 to G5, Figure 1), identified through hydrological analysis (ESA 2019) as areas expected to experience similar effects from the proposed project. Each group consisted of six tree and shrub species selected to represent a range of sensitives to flow conditions. A total of 97 trees were monitored in total. The species monitored were Arroyo Willow, Black Willow, Sandbar Willow, Mule Fat, Blue Elderberry, California Sycamore and are hereafter referred to as “trees”.

Stem water potential (SWP) and canopy volume (CV) were used as short term and long-term indicators of stress on the riparian plant community, as a proxy for LBV habitat. In addition, several other climatic and physical factors (Table 1) that may affect SWP and CV were routinely measured.

An annual (i.e., of two monitoring events per year) analysis of the monitoring data evaluates changes to SWP and CV and whether a trigger value has been met that may initiate an increase in flows back to baseline conditions. The trigger value is determined as a significant (*p* < 0.1) decline within a group or species condition based on standard paired (baseline with current) t tests.

NB: Trigger values for any individual parameter in any individual vegetation alliance or AMP group alone, however, may not be cause for implementing the adaptive management actions of increasing water delivery, per the AMP.

### Monitoring Data

The structure of the monitoring data (Figure 2) exhibits a hierarchical nature, primarily attributed to the identified habitat groups as well as the various species monitored. Discharge measured from the gages and effluent discharge points were assigned to specific groups within the study area. Monitoring took place twice per year, in spring and fall, with three years of baseline data collection (2018-2020, noting that only the Fall season was monitored in 2018), plus two years effects monitoring (2021-2022) following reduced WRP discharge in 2020. The baseline dataset contained one wet and one dry year, both years in the post-reduction dataset were dry years. Wet and dry years were defined as above or below project area average of 14.94 inches of rainfall, respectively. Monitoring was conducted in spring and fall, to capture elements of the annual hydrograph with spring representing the wet season and fall representing the dry season.

A diagram of a tree

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Figure 2: Structure of monitoring data. Species - AW; Arroyo Willow, BW; Black Willow, SW; Sandbar Willow, MF; Mule Fat, BE; Blue Elderberry, SY; California Sycamore. SWP; Stem Water Potential, CV; Canopy Volume. Note that group 5 receives a proportional amount of flow from all WRPs. See methods for details

#### Stress indicators

The 97 trees were monitored for two stressor indicators.

Stem water potential (SWP) is the pressure tension expressed in “atmosphere” required to express a droplet of water from the fresh cut end of a sample leaf. SWP is a proxy for water availability, and if the tension exceeds the ability of the plant to make the night-time recovery, the water column in the plant can cavitate, leading to permanent wilt and leaf and stem death. A *higher* value of SWP indicates a higher level of stress and is associated with short-term desiccation. Detection of SWP stress serves as an advance warning of stress for the entire area, and the warning will be provided in sufficient time to implement adaptive management to reverse the stress before the mortality of the vegetation is threatened. Add how is was measured?

Canopy volume (CV) estimated the percentage of the live canopy in the sampled individual plant. Canopy dieback may result from drought any time during the growing season, and alternatively normal senescence or insect injury. A *lower* measure of canopy volume indicates a higher level of stress. CV provides an integrative measure of tree health over time and responds more gradually to sustained desiccation.

#### Stressor variables

The modeling analysis incorporated all stressors and variables collected during the monitoring process (Table 1). Precipitation (RainFallMod) and air temperature (TempMeanModF) were sourced from PRISM (available at https://prism.oregonstate.edu/) for all years corresponding to the monitoring data for the Whittier Narrows area (800mx800m grid).

The discharge measured from gages (Q) and WRP Q (single and combined outfalls) was allocated to groups as outlined in Figure 2. The amount of flow received by group 5 was not measured, therefore, to retain its inclusion, a constant value of 0.01 was allocated. We conducted a sensitivity analysis on various static and proportional flow values, leading to the conclusion that 0.01 was appropriate for application (see Appendix A1).

Many trees had been replaced over the monitoring period, the majority were removed through flood control maintenance activities, and some trees were damaged by other human activities (e.g., fire, Wood 2022). Furthermore, on occasion, damage (18 trees [18%]) was observed to certain trees, but replacements were not made. To consider replaced trees and tree damage in the model as stressors, we generated binary variables to denote replacement (yes or no) and damage (yes or no). Once a tree was identified as damaged, this classification remained consistent throughout the remainder of the dataset unless the tree underwent replacement. This approach facilitated the examination of the effects of tree damage on subsequent analyses, ensuring that damaged trees were appropriately accounted for in the dataset. However, we conducted a sensitivity analysis that suggested no significant influence of damaged trees in the model outcome (see Appendix A2).

Several of the variables described contained missing values, therefore, to preserve the volume of data points, any missing values were imputed using a proximity matrix approach (randomForest package R, Breiman 2001). This approach is an iterative method that imputes a weighted average of non-missing values for continuous variables. For categorical variables a value most similar to non-missing values is estimated, according to the associated data.

The analyses were conducted on the observed stressor indicator values of SWP and CV (unless specified as not “Monitoring Data” in Table 1). Additional to analyzing absolute observed values, we analyzed the relative change in stressor indicator, i.e., annual changes, to account for year-to-year variations. However, this analysis was less effective compared to the use of observed values (see appendix A3).

Table 1: All stressors with values, description, and sources. Final column denotes it’s use in the final Random Forest (RF) model. Stars indicates variable had missing data.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Stressor Variable | Values | Description | Source | Used in final RF model |
| Species | AW; Arroyo Willow, BW; Black Willow, SW; Sandbar Willow, MF; Mule Fat, BE; Blue Elderberry, SY; California Sycamore | species selected for monitoring | Monitoring data | SWP, CV |
| Group | 1 to 5 | Sample locations with identified differences in riparian coverage and hydrology | Monitoring data | SWP, CV |
| Year | 2018-2022 | Years monitoring data collected | Monitoring data | SWP, CV |
| Season | Fall, Spring | Seasons monitoring data collected | Monitoring data | SWP, CV |
| Tree Position | L; Low, M; Middle, H; High, ML, LM, | Relative position of plant ID (tree) to active stream channel | Monitoring data | SWP, CV |
| Substrate\* | Fines, Gravel, Cobble, Stone, Boulder, Bedrock | Substrate at each tree or shrub | Monitoring data | SWP, CV |
| Damage | Yes, No | An instance of damage was observed but without replacement | Monitoring data | SWP, CV |
| Tree replaced | Yes, No | Tree that has been replaced from previous monitoring surveys due to damage | Monitoring data | SWP, CV |
| Distance To SJC\* | Meters | Water course distance from individual tree to San Jose Creek WRP outfall | GIS | SWP, CV |
| Stream Flow | Monthly (MGD) | Discharge from gages, allocated to specific groups | Monitoring data | SWP, CV |
| Discharge: SJC | Monthly (MGD) | Discharge from San Jose Creek WRP outfall | Monitoring data | SWP, CV |
| Discharge: WN001 | Monthly (MGD) | Discharge from Whittier Narrows WRP (1) outfall | Monitoring data | SWP, CV |
| Discharge: WN002 | Monthly (MGD) | Discharge from Whittier Narrows WRP (2) outfall | Monitoring data | SWP, CV |
| Discharge: POM | Monthly (MGD) | Discharge from Pomona WRP outfall | Monitoring data | SWP, CV |
| Discharge: SJC & POM | Monthly (MGD) | Combined discharge from San Jose Creek and Pomona WRPs | Monitoring data | SWP, CV |
| Discharge: SJC, POM, & WN1 | Monthly (MGD) | Combined discharge from San Jose Creek, Pomona and Whittier Narrows WRPs | Monitoring data | SWP, CV |
| RainFallMod | Monthly mean (mm) | Modelled Precipitation | PRISM | Not used |
| Rainfall Intensity\* | Monthly mean (inches) | Observed Precipitation | Monitoring data | SWP, CV |
| TempMeanModF | Monthly mean (degrees F) | Air Temperature | PRISM | Not used |

### Modelling approach

The primary aim of the modelling analysis was to assess how WRP discharge, and the supplementary stressor variables (stressors), affect SWP and CV (stress indicators), with the intention of evaluating the effectiveness of the current monitoring strategy and determining whether any adjustments are warranted. In alignment with the AMP objectives, we aimed to answer the following questions:

1. Which stressors have most influence on the stress indicators?
2. How sensitive are stress indicators to stressor and physical parameters collected?
3. How much of the change to stress indicators can be explained by WRP discharge?
4. How much future monitoring is needed to detect a significant change?

Several statistical analyses were conducted on each of the stress indicators SWP and CV following an adaptive, iterative process to address questions from the HMC members (Figure 3). Questions were broadly grouped into explanatory questions that aimed to understand relationships between physical factors and biological response; predictive questions to help anticipate how management decisions would affect biological conditions; and power analysis to help inform changes the monitoring program so increase sensitivity to stress-induced changes. All analysis was conducted in R Statistical Programming version 4.4.1 (R Core Team, 2024).

A diagram of a flowchart

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Figure 3: Modeling sequence used to address Adaptive Management Plan (AMP) related questions. Red boxes are questions posed by the Habitat Management Committee (HMC), Green boxes represent the approach taken and purple boxes are the method together with how the outcome that answered the question.

#### Explanatory Model approaches

##### Random forest model approach

A Random Forest model (RF) is a machine learning technique based on decision trees (Breiman, 2001; Liaw & Wiener, 2002), well-suited for handling complex ecological datasets (Simon et al., 2023, Pichler & Hartig, 2023). They are non-parametric in nature, so are apt at finding connections between predictors and response variables. However, they do not identify mechanistic links within the system. In this analysis, we apply a regression RF to the stress indicators SWP and CV, utilizing the complete set of predictors as specified in Table 1. Analysis was conducted using packages randomForest and rfUtilities (Evans et al., 2011; Evans & Murphy, 2018; Liaw & Wiener, 2002)

We extracted the variable importance of the initial full model and used it to streamline the predictor set, retaining only those with a positive influence (greater than 0). Subsequently, a reduced RF model was constructed (final model), incorporating only the predictors with positive importance. The importance of variables was assessed using the mean decrease in accuracy, however for ease of interpretation and visualization, we report the variable importance as a relative importance, calculated by converting mean decrease in accuracy to percentage. It is important to note that variable importance can be interpreted as the variables most critical to model performance and prediction but does not imply causal relationships within the data. The final column of Table 1 indicates whether each predictor was retained in the final model for each stressor indicator (SWP, CV).

For validation and evaluating model performance, several key metrics were utilized. The variance explained (%), was used where higher values signifying better model performance and the Mean Square Error (MSE), which is an absolute measure with lower values indicating better performance.

The RF algorithm inherently includes an internal validation procedure, by training the model on a subset of the data at each tree and testing the predictions on the remaining data. To supplement this, an additional cross-validation process was conducted, which involved K-fold cross-validation, where 10% of the data was set aside as testing data, and the model was trained on the remaining data (training data). This process was repeated 99 times to estimate the error. Through this process, the Root Mean Square Error (RMSE) was reported as a measure of error, calculated by comparing observed and predicted values, and it is expressed in the same unit as the response variable (i.e., SWP, CV).

##### Mixed effects model approach

Due to the grouped nature of the monitoring data (Figure 2), we performed a mixed effect model. A mixed effects model is a linear regression approach that accommodates grouped data structures, consisting of fixed effects and random effects. Fixed effects are predictors and stressor employed in the same way as a standard linear regression. Random effects are factors that consider the grouping structure of the data (e.g., group) that allow for variation in the different levels of the group (e.g., group 1, group 2 etc.). The random effect component of this modelling technique is well suited to the data structure for the SGR AMP.

Only predictors and stressors from the reduced RF model were retained, which included eliminating variables with negative importance in the reduced model. Variables exhibiting a strong correlation (> 0.9), can introduce multicollinearity into the model. Multicollinearity, in turn, undermines the reliability of parameter estimates and can complicate the interpretation of model results. Considering this concern, only one outfall discharge variable was included in the model (i.e., Combined SJC & POM discharge correlated with SJC; r = 0.98, and combined SJC, POM & WN; r=0.97). The included variable was determined through variable importance and a sensitivity analysis that conducted a mixed model on each of the outfall discharge variables, ensuring no or limited difference in model outcome. This action aligns with best practices in data preprocessing, aimed at mitigating multicollinearity and thereby enhancing the dependability and interpretability of the model.

All continuous stressors were included as fixed effects in the analysis and were scaled between values 0 and 1 for easy comparison. Predictors associated with the data structure were tested as random effects, specifically Species, Year, group, and Season. The Intraclass Correlation Coefficient (ICC) was used to assess whether values within a group were as similar as those between groups. If values were similar, the group was excluded as a random effect and included as a fixed effect. Conversely, if values exhibited differences, the group was retained as a random effect. Mixed model analysis was conducted using lme4, performance, and lmerTest (Bates et al., 2015; Kuznetsova et al., 2017; Lüdecke et al., 2021; Luke, 2017)

Model performance and significance were evaluated to assess the accuracy and reliability of the analysis. Comparing the performance of the models for SWP and CV stress indicators provides insights into their relative sensitivity to physical parameters included in the model. This information helps us understand which indicator may be more responsive to change. Additionally, this evaluation helps identify the individual effects of each physical parameter on both stress indicators to understand which stressor drives the observed impacts. To achieve this, we used R-squared to understand the proportion of variance explained by the model and the Intraclass Correlation Coefficient (ICC) to quantify the amount of variance explained by the grouping structure in the analysis. In addition, P-values were used to determine the significance of predictors, with values less than 0.05 signifying statistically significant predictors.

#### Predictive Modelling Approach

##### Probability of increased stress

To predict the probability of increased stress resulting from reduced discharge, we applied logistic regression to associate the alteration in discharge with the corresponding change in stressor response. Discharge alteration was calculated as the change (delta) discharge from baseline to current. The analysis assumes any change in stressor indicator values from baseline to current as significant. Importantly, to calculate a delta value, trees needed to be present in both baseline and current years, therefore original and replacement trees that don’t appear in both time frames, were excluded (remaining trees; n= 67).

Baseline discharge values were determined as the median discharge observed during the years 2018 to 2020, preceding the implementation of discharge reduction measures. Conversely, current discharge values were computed as the median discharge recorded in the years 2021 and 2022. The delta discharge was subsequently derived as the disparity between these two values. Similarly, baseline SWP and CV were established as the median values across the baseline period (2018-2020). The alteration in stressor indicator was then categorized as a binary variable (1,0), denoting either an increase (1) or a decrease (0) in stress relative to the median baseline value. In addition, we calculated delta discharge for water year type (i.e., wet and dry years) however, although the baseline data includes both wet (2019) and dry years (2020), only dry years were present in the current data (2021 & 2022). Wet and dry years were defined as above or below project area average of 14.94 inches of rainfall.

Group 5, characterized by minimal to negligible influence from discharge outfalls, and encompasses a consistent imputed value of 0.01 across both baseline and current conditions. Consequently, group 5 was excluded from this specific analysis due to its distinct behavior and negligible variability in response to outfall discharge.

Logistic regression was subsequently employed to analyze the delta stressor indicator, utilizing solely the delta discharge as a predictor. This choice of predictor was informed by the outfall discharge metric, identified through variable importance and use in the mixed effects models, thereby ensuring consistency across the analyses. The model was applied to all stressor indicator values together, and for each species individually. To assess performance, McFaddens R2 (McFadden, 1979) was applied, which serves as a pseudo R2 metric commonly used to evaluate the performance of logistic regression models. While its scale spans from 0 to 1, it typically ranges from 0 to 0.4, with values between 0.2 and 0.4 indicating a very good fit (Louviere et al., 2000, Mcfadden, 1979).

##### Statistical Power Analysis

Statistical power analysis was conducted to determine the required sample size for detecting a significant impact on stress indicators through changes in discharge. This analysis employs an effect size, a significance level (alpha), and a target statistical power level to establish an optimal monitoring duration for the study. The significance level was set at 0.05, and the desired statistical power level was defined as the standard value of 0.8.

The effect size was determined through two distinct approaches. First, it was computed using the correlation coefficient between delta stressor indicator values and the delta discharge metric calculated above. This approach provides insights into the timeframe required to detect a significant discharge-related effect on each stressor indicator, presented through a power curve that visualizes statistical power for different monitoring durations. This analysis was conducted by applying the delta values as described above. Thus, any alteration in stress indicators served as our metric for significant changes in stress. As this analysis uses delta (i.e., the change from baseline to current discharge) it adheres to the same caveats outlined for the predictive analysis, including the removal of group 5. That means only 67 trees could be used in this analysis.

Secondly, the effect size was estimated using Cohen's d, comparing stress indicators from before the project's implementation (in 2020) to the most recent complete year (2022). As this analysis compared indicator across years, the observed values were applied. This approach informs us about the monitoring duration needed to detect a significant change in each stressor indicator, regardless of reduced flow. This information is presented as a single value indicating the number of years required, maintaining a statistical power of 0.8 and an alpha level of 0.05. Since this analysis does not use delta flow values, the full number of trees (n=97) was included in this analysis.

Although a significance level of 0.05 is traditionally used, it is not necessarily required and may be too stringent for this analysis given the inherent “noise” in the data set. Therefore, we performed a sensitivity analysis on both the power analyses by applying different significance levels (alpha; 0.05, 0.1, 0.15, 0.2, 0.25). This information is presented as a curve showing the relationship between the significance level and the corresponding estimates from the power analysis.

Power analysis was conducted using packages pwr and WebPower (Champely, 2020; Zhang & Mai, 2023).

## Results

To illustrate the process of applying modelling techniques to aid AMP decision making, we show

results for SWP, however all results for CV are in the appendix (see appendix A4).

### Explanatory modeling

The RF model for observed SWP demonstrated strong performance, accounting for 92% of the variance with a Mean Squared Error (MSE) of 0.82. Notably, the five most influential predictors, for model performance, in this analysis were Species, Season, Year, Distance to SJC and group (Figure 4). It's worth mentioning that while modelled rainfall (RainfallMod) initially exhibited slightly positive predictor importance in the full model, it displayed a negative importance in the reduced model due to the removal of variables that contributed to noise in the model, leading to its exclusion from the subsequent mixed effects model analysis. The k-fold cross-validation also performed well showing a median RMSE of 0.93 (± 0.001), which provides additional evidence of the model's effectiveness and reliability.

A graph with black dots

Description automatically generated

Figure 4: Relative importance for stem water potential l(SWP) predictors in the reduced model. Abbreviations; SJC, San Jose Creek; POM, Pomona; WN, Whittier Narrows

The mixed effects model also exhibited strong performance as indicated by an R-squared value of 0.65 (Table 2). In this model, two random effects of Species and Season were employed. While several predictors displayed highly significant relationships with SWP, i.e., <0.001 (Table 2), it's worth noting that predictors describing discharge, whether measured from stream gages or effluent discharge points, showed no statistical significance (i.e., <0.05). Despite its high importance in the RF model (Figure 4), distance from SJC did not show a statistical significance. SWP displayed a consistent relationship across all species in response to combined SJC & POM (except for Blue Elderberry (BE), which showed a positive relationship) with Mule Fat (MF) demonstrating the highest SWP values (Figure 5). See appendix (A5) for estimates and relationships with SWP.

A graph of different colored lines

Description automatically generated

Figure 5: SWP as a function of combined Q from SJCand POM per species (AW; Arroyo Willow, BE; Blue Elderberry, BW; Black Willow, MF; Mule Fat, SW; Sandbar Willow, SY; California Sycamore).

Table 2: Mixed effects model performance and significance for stem water potential.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| *Rsq* | *ICC* | *Fixed Effect Predictor* | *Significance* | *Relationship* |
| 0.65 | 0.63 | Stream flow | no | - |
| Discharge: SJC & POM | no | - |
| Tree replaced | no | - |
| Year | Yes | Varied: Lower in 2022 than 2018 |
| Group | Yes | SWP increases with group number |
| Distance To SJC | No | - |
| Substrate | Yes | Varied: SWP highest in Bedrock and Cobble |
| Tree Position | Yes | SWP highest in Medium |
| Rainfall Intensity | No | - |
| Damage to Tree | Yes | SWP higher in damaged trees |
| ***Random Effect Predictor*** |  |  |
| 0.44 | Species | NA | Higher in Mule Fat |
| 0.19 | Season | NA | Higher in Fall |

### Predictive modelling

#### Probability of increased stress

The outfall discharge metric applied in this analysis was the combined SJC & POM discharge. Changes in outfall discharge in 2020, resulted in an overall median increase of 2 MGD (Million Gallons per Day), however changes in seasonal discharge demonstrate a median increase in fall (November to April). discharge of ~ 5 MGD and a median reduction of ~12 MGD in spring (May to October) discharge.

The predictive logistic regression for overall SWP exhibited low to moderate performance, yielding a Nagelkerke R2 of 0.09. The statistical analysis revealed a negative relationship, indicating that an increase in discharge from baseline conditions leads to a reduction in SWP values (Figure 6). Considering the robust seasonal effect observed in both the RF and mixed effects model, alongside the significant discrepancies in delta discharge across seasons, it becomes evident that discharge reductions may exhibit greater sensitivity during spring compared to fall. Moreover, the predictive analysis underscores a stronger association between changes in discharge and SWP compared to absolute values, which is reflected in the absence of significance in the RF and mixed model. Consequently, the overarching implication is that reducing discharge is likely to increase the probability of a stress response in SWP. It is important to note that the analysis considers any change in SWP as a stress-response, which should be considered when interpreting the results of this analysis.

A diagram of a diagram showing different types of discharges

Description automatically generated with medium confidence

Figure 6: probability of increased SWP stress, overall and in dry years due to outfall discharge. Grey dashed line is the baseline discharge from years 2018-2020, red area is the median current combined discharge from years 2021-2022. Green dashed lines are the median delta combined discharge from 2021-2022 for fall and spring.

The 2021 and 2022 monitoring years were dry years. Therefore, we could not compare differences in the probability of stress between water year type (wet vs dry). Nonetheless, we compared the probability of stress during dry years for SWP. Rainfall in 2021 was 145.3mm, and 301.5mm in 2022 (Wood, 2022). Although 2022 was wetter than 2021, the probability of stress is lower for a similar reduction in flow (Figure 6). Model performance for both years was low (2022; 0.05, 2021; 0.07).

The probability of stress predicted per species for SWP performed especially well for California Sycamore (SY, Figure 7), yielding a Nagelkerke R2 of 0.52. Blue Elderberry (BE), Black Willow (BW) and Mule Fat (MF) performed better than the overall model, however performance remained relatively low (R2 : 0.13-0.16).

A graph showing different colored lines

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Figure 7: Probability of SWP stress as a function of combined discharge (SJC & POM) per species (AW; Arroyo Willow, BE; Blue Elderberry, BW; Black Willow, MF; Mule Fat, SW; Sandbar Willow, SY; California Sycamore).

#### Statistical Power Analysis

The correlation coefficient for delta SWP and delta combined discharge (or Q) (SJC& POM) was a moderate value, while delta CV was much smaller (SWP: -0.33, CV: -0.067). The value for SWP held significance, and the determined required monitoring duration to observe a significant influence of delta discharge (at p<0.05) is expected by 2023, i.e. one additional year of monitoring (Figure 8). The value for CV did not hold significance at the current sample size with a projection of significant influence of delta discharge being undetectable until 2035. However, if the sample size was doubled, i.e., 134 trees sampled per season (268 per year), then the projection decreases to 2029 (assuming that many trees are available). However, additional trees will not enhance the predictive model since they were not represented in the original data set.

The Cohen’s d approach, which detects change over time associated with the inherent variability in the system showed a Cohen’s d value for SWP of 0.14 with an estimated additional 4.2 years of monitoring to see a significant change. Conversely, for CV (Cohen’s d; 0.09) the power analysis estimated a need for an additional 9.1 years to detect a significant change. This indicates that variability associated with change over time exceeds the influence of changes in discharge.

The disparities observed across analyses stem from the contrasting methodologies employed in utilizing delta values to compute the correlation coefficient versus employing observed values for calculating Cohen’s d.

A graph showing the difference between the same model

Description automatically generated with medium confidence

Figure 8: Statistical power analysis for CV and SWP in relation to delta Q measured from gages. Red dashed lines indicate the standard statistical power value of 0.8 and corresponding year of monitoring, based on the current sample size (n=67 trees per season, i.e., 134 trees per year)

The sensitivity analysis revealed trade-offs between significance levels and the amount of additional monitoring required. The correlation coefficient approach suggests that a significance level of 0.3 for CV can be achieved by 2027 (Figure 9). For SWP, all significance levels are achievable by 2023 (Figure 9). The Cohen's D approach (Figure 9) indicates that an additional four years of monitoring are needed to achieve a significance level of 0.3 for CV, aligning with the correlation coefficient result. However, a significance level of 0.05 for SWP is achievable in approximately the same additional four-year timeframe.

A comparison of a plot of a person's level

Description automatically generated with medium confidence

Figure 9: Sensitivity of significance levels though the Cohen’s D approach (n = 97 trees per season, 192 trees per year) and correlation coefficient approach (n=67 trees per season, 134 trees per year) applied on delta flow values. Year refers to the first year the significance level is expected to be reached with additional monitoring (2 seasonal surveys per year).

### *Discussion*

We applied a combination of statistical models to assess how reductions in discharge from the WRP may influence riparian vegetation, focusing on stress indicators SWP and CV. Our models evaluated the influence of various physical factors, predicted tree stress under different discharge conditions, and determined the duration of monitoring needed to detect significant changes in these stress indicators. Results showed that SWP was more responsive than CV to reductions in flow, although no significant relationship was found with reduced flow and tree stress.

By employing modeling early in the AMP process, we were able to refine the monitoring process more quickly. After just five years of monitoring, three baseline years and two years post-discharge reduction, modeling enabled us to adjust the AMP by allowing data interpretation and refinement of adaptive process to occur sooner than what have otherwise been possible. For example, the Columbia River Adaptive Management Program was able to make initial adjustments after the first 13 years of monitoring from an ongoing plan that has been going on for 25 years thus far (Littles, et al. 2022). Furthermore, involving the HMC in the iterative development and interpretation of the modeling helped foster a clearer understanding of how the modeling results could support decision-making, building confidence in the process. Ideally, model development should be integrated from the very beginning of an adaptive management project (Cartwright, et al. 2016, Irving et al in review), even during conceptual stages. This approach enhances the effectiveness of adaptive modelling in optimizing management strategies and informing adaptive monitoring efforts (e.g., Dai, et al. 2025).

#### How Modelling has Informed Adaptive Management

Our study demonstrates that modelling can play a crucial role in adaptive management by informing key aspects of decision-making, particularly in relation to monitoring strategies, indicator sensitivity and the influence of flow reductions (Table 3).

First, we were able to identify the most responsive stressor indicator, i.e. SWP, to flow reduction and other physical factors, making it a better early indicator of plant stress. This discrepancy in sensitivity is likely attributable to SWP's responsiveness to shorter time frames, whereas CV may require more time to reflect observable effects. Nonetheless, this is valuable for adaptative management, as focusing on the most responsive indicator can enable early detection of ecological impacts. In addition, California Sycamore was identified as potentially a good early indicator of SWP stress.

Second, we were able to demonstrate and understand system variability, which lead to improvements in the monitoring plan. Variables associated with the monitoring design (Species, group), site characteristics (Substrate, tree position), and temporal factors (Year, Season) explained the most variation in stress. Climate-related factors and WRP discharge had little influence on plant stress, indicating that inherent system variability and non-flow-related factors are significant contributors to plant stress. While understanding which species or group are more sensitive to change in flow is valuable for monitoring strategies, the high level of system variability may obscure the potential effects of reduced flow. Addressing this challenge requires adjustments to monitoring design or measurement strategy (Steel et al 2013). For example, incorporating control or reference sites could help distinguish between natural fluctuations in the system and change directly attributed to flow reductions.

Third, we were able to inform resource allocation by highlighting that group 5 contributed little to understanding flow-related impacts. This issue caused the HMC to consider removing group 5 from monitoring, which would save time and resources, allowing for more focused data collection on groups more responsive to flow changes.

Fourth, our power analysis provided a timeline for detecting significant changes due to reduced flow. For SWP, we project that significant impacts will be detected by 2023, however detecting changes in CV may take much longer – potentially until 2035 under the current monitoring plan. However, this analysis also allowed for earlier consideration of the effects of sample size and consideration by the HMC to increase the number of trees monitored to improve the power to detect changes. Without the use of models, this decision to increase the sample size would have been deferred to later years thereby reducing the opportunity to collect additional data early in the monitoring program.

Fifth, the analysis compelled the HMC to develop a clearly defined decision matrix (Figure 10). The matrix consists of a clear, objective series of decision points and associated actions. The intent is to provide a roadmap for current and future HMC members to evaluate monitoring data and make recommendations in a transparent manner as intended by the AMP. Development of the decision matrix included consideration of additional variables not originally included in the AMP (e.g., soil moisture) and modification of existing variables to improve their sensitivity. Ultimately, the decision matrix should allow the HMC to more ready determine when flows should be adjusted to ensure ecological goals are realized.

Sixth, the analysis questioned the appropriateness of the current trigger values outlined in the AMP, which rely on detecting a significant (*p* < 0.1) decline within group or species condition using standard paired t tests (baseline vs. current). While this trigger value has been useful for evaluating general changes in the stress indicators, it does not account for how much of the observed change is directly attributable to reduced discharge. Insights gained from the modeling analysis revealed that the system’s inherent variability could obscure the potential impacts of flow reduction. Based on this understanding, the decision matrix was designed to incorporate the inherent variability and nuances within the system as highlighted by the modeling analysis.

By identifying the most responsive indicators, understanding system variability, and informing resource allocation and monitoring duration, necessary adjustments can be made to the monitoring strategy, refining the quality of the data collected. This, in turn, enhances the quality of data fed into the predictive models, improving model performance. This is particularly important as the current predictive model is sub-optimal and requires improvement before it can reliably inform management decisions.

Table 3: Overview of questions asked, model applied (sample size), results for Stem Water Potential (SWP) and Canopy Volume (CV) with conclusions and how the result informed the AMP.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Question | Model Approach | SWP | CV | Conclusion | Informing AMP |
| Which stressors have the most influence on the stress indicators? | Random Forest (97) | Flow related variables show low importance | Flow related variables show low to moderate importance | Inherent variability in system most influential in model | Modifications to monitoring plan e.g., control/reference sites. Informs decision matrix |
| How sensitive are stress indictators to physical parameters? | Mixed Effects Model (97) | Varied with year, group, substrate, position and tree damage | Weak performance, slight significance of flow effect | SWP; inherent variability in system most influential in model. CV: additional data needed for conclusive results | SWP a better early indicator. Informs decision matrix |
| How much stress can be explained by WRP Q? | Predictive Logistic Regression (67) | Weak-moderate predictive performance shows a negative relationship. California Sycamore model showed high predictive performance with strong negative relationship | Unable to determine relationship as model performance very weak | Need more data for conclusive results. California Sycamore may be a good indicator of reduced flow impacts on SWP | SWP a better early indicator. Potential removal of group 5. Informs decision matrix |
| How much additional monitoring needed to detect a change? | Power Analysis (Corr coefficient = 67, Cohen's d = 97) | 1-4 years of monitoring | 7-13 years of monitoring with increase in sample size | CV likely needs far more additional monitoring than SWP | Increase the number of trees sampled. |

#### Assumptions and caveats

While our modelling provided valuable insights, some caveats must be considered. First, some key physical factors influencing plant stress, such as soil moisture, were not included in the monitoring plan may play a more significant role in driving plant stress compared to the surface water parameters collected. Second, the predictive model assumes that any change in SWP is an indication of stress, however without a clearly defined threshold for stress this could lead to overestimations. Developing specific trigger values for stress would improve the model’s precision.

#### Wider implications

A more variable climate means that environmental changes, including changes to river flows, may occur more rapidly and conventional (potentially slow) adaptive approaches may therefore need rethinking.

To be transformative, adaptive management must be proactive and anticipatory rather than reactive (Capon et al. 2018). More frequent and severe drought cycles associated with climate change and exacerbated by urban growth make adaptive management extremely challenging. Increasing demands on limited water resources, changing water use practices, extreme interannual variability and trends toward drier and flashier systems (rapidly changing flows) make it difficult for monitoring programs to discern management effects from effects of other stressors. Models that can predict likely outcomes of management interventions under different climate scenarios and differentiate effects of multiple co-occurring stressors are, therefore, likely to become increasingly valuable adaptive management tools (Webb et al., 2018).

Sustained relationships are necessary to accomplish long-term management goals (Littles et al. 2022). Individual representatives of various stakeholder groups (e.g. agencies) will change over time, particularly during the course of long-term monitoring programs. Therefore, careful documentation of the AMP, including the modeling, process is essential to ensure continuity over time. This is particularly true when modeling is used to support decisions regarding adaptive monitoring and management. The assumptions, approach, and rationale behind the interpretation of model outputs must be clearly documented to ensure that future staff have an understanding of and confidence in earlier decisions and can build upon them as monitoring and AMPs progress over time. Including modeling experts on habitat management committees that oversee AMPs can aid in developing clear expectations of the study and helping to build consensus on shared outcomes (Irving et al in review). Coupling the use of models and empirical observations can allow AMP decision processes to be updated iteratively to improve certainty and predictability in the decision-making process (McLoughlin et al. 2020). Figure 10 demonstrates how the decision-making process for the AMP gained clarity (and complexity) based on improved understanding that resulted from the modeling.

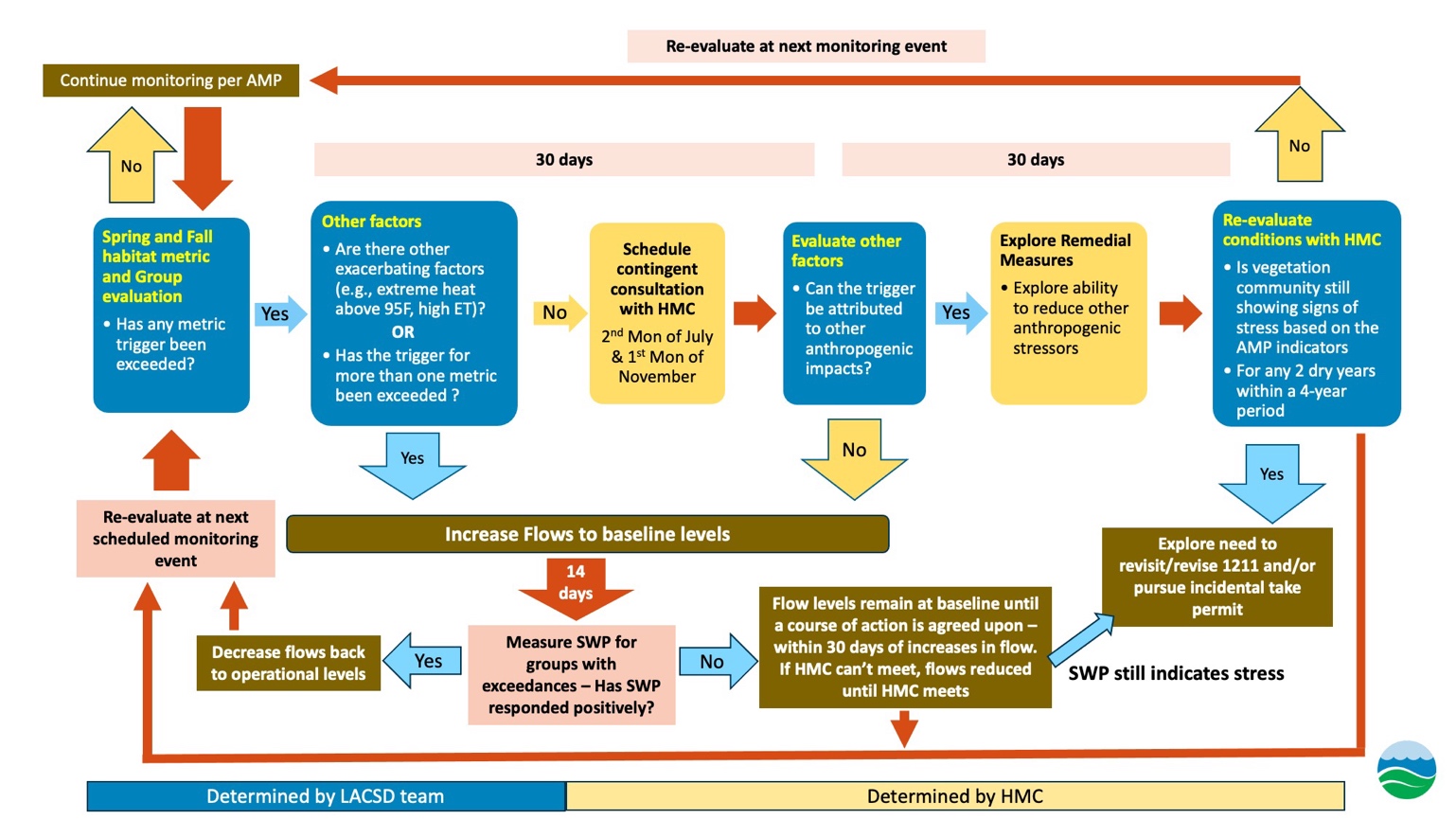


Figure 10: Evolution of the AMP decision making process based on outcomes of the adaptive modeling analysis with key findings from previous monitoring events and natural changes to the habitat over time. NB. 1211 refers to the wastewater change petition under which the permit to reduce flows was issued.

### Conclusion

Modeling can help accelerate the adaptive management process by using early monitoring results to project potential future patterns and anticipate potential effects of management actions. This will allow earlier intervention and adjustment to improve effectiveness of monitoring programs and subsequent management decisions. For example, augmenting SWP with soil moisture to improve sensitivity, increasing the number of trees to detect trends sooner. Modeling can also provide earlier insight into indicators that provide sufficient sensitivity vs. those that don’t and opportunities where early increases in monitoring frequency or intensity can increase the ability to draw defensible conclusions sooner.

Coupling modeling and directed monitoring (informed by modeling results) can also help focus on areas where additional monitoring would be most beneficial or potential high impact areas. Incorporating modeling from the onset of the AMP development process and integrating it into a combined monitoring-modeling workflow will ultimately result in more effective and efficient monitoring that is able to support AMP decisions.

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### Appendix

#### A1: Sensitivity analysis on proportional flow

A sensitivity analysis was performed to evaluate the impact of different proportional flow allocations to group 5. Five distinct proportions were tested (1%, 2%, 5%, 10%, 20%), and the variable importance and explained variance of all predictors (including combined variables) were compared against those using a constant value. Due to the type of analysis applied (i.e., machine learning), some variation between models runs is expected, even when applied with the same data. Any variation beyond expected levels would result in changes to overall patterns and significant changes in model performance (i.e., more than 1 or 2 points).

The sensitivity analysis assessed the influence of various flow proportions allocated to group 5. While some variation in relative importance was noted, no significant changes in the overall patterns or individual variables were observed across the different flow proportions for either SWP (Figure A1a) or CV (Figure A1b). Additionally, the model with a constant value of 0.01 for group 5 performed best overall. Therefore, we continued the remainder of the analysis with the constant value.

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Figure A1a: SWP sensitivity of proportional flow for group 5. ProportionF = level of flow, RFValExpl = variance explained from the random forest model.

A graph showing the number of different types of plants

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Figure A1b: CV sensitivity of proportional flow for group 5. ProportionF = level of flow, RFValExpl = variance explained from the random forest model.

#### A2: Sensitivity analysis on damaged trees

A sensitivity analysis was conducted to evaluate how damage affects stress indicators for trees influenced by human activity. Comparing model runs with and without damaged trees (18 trees [18%]), we found no significant difference in the model outcome. This result is attributed to the similar performance and comparable main patterns observed in both scenarios and the fact that SWP captures some of the effects of tree damage (Figures A2a, A2b)

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Figure A2a; Mixed model on SWP without damaged trees

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Figure A2b: CV mixed model without damaged trees.

*A3: relative change of response variable*

The analysis was initially performed using the observed values of each stressor response. However, due to the repeated measurements of individual trees over time, the models were also applied to a relative change variable. This relative change was computed from one observation to the next, starting at 1. A lower value signifies a reduction in the stressor, while a higher value indicates an increase in the stressor value. By incorporating this relative change variable, the analysis aimed to capture temporal variations in the stressor response, providing a more comprehensive understanding of its dynamics over time.

The RF analysis conducted on the relative change in SWP demonstrated relatively weaker performance, accounting for only 77% of the variance with an MSE of 0.02. The five most important variables for model performance in the relative model matched those of the observed SWP model, albeit with “Year” emerging as the most important variable (Figure A3a). This shift in importance is likely due to the temporal factors introduced from the relative SWP calculations.

The mixed effects model, incorporating random effects of Year and Season, was applied to the relative change dataset. However, the analysis yielded a notably low performance, with an R2 value of 0.12. Consequently, due to its limited explanatory power, this analysis was excluded from the overall assessment.

The RF analysis conducted on the on the relative change in CV demonstrated slightly weaker performance, accounting for 80% of the variance with an MSE of 0.17. Similar to the relative SWP model, the five most important variables, for model performance, in the relative model matched those of the observed CV model, albeit with “Year” emerging as the most important variable (Figure A3b). Again, this shift in importance is likely due to the temporal factors introduced from the relative CV calculations.

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Figure A3a: Relative importance of relative change in SWP

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Figure A3b: Variable importance of relative change in CV.

*A4: Canopy Volume model results*

The RF model for canopy volume delivered strong performance, explaining 81% of the variance, with MSE of 60. Among the predictors, Year, Species, Season, Distance to SJC 002, substrate and group were the most influential (Figure A4a) for model performance. Notably, all predictors retained for the mixed effects model were consistent with those employed in the SWP model. The k-fold cross-validation also performed well showing an RMSE of 8.02 (± 0.21), which provides additional evidence of the RF model's effectiveness and reliability.

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Figure A4a: Predictor importance for canopy volume. Abbreviations; SJC, San Jose Creek; POM, Pomona; WN, Whittier Narrows

The outfall discharge metric applied in this analysis was the combined SJC& POM discharge. The mixed effects model exhibited a relatively weaker performance than that of SWP, as indicated by an R-squared value of 0.23 (Table A4). In this model, a single random effect related to Species was employed. While several predictors displayed significant relationships with CV, it's worth noting that predictors describing discharge measured from gages did not demonstrate statistical significance, however discharge measured from effluent discharge points, demonstrated a weakly significant relationship. CV displayed a consistent relationship across all species in response to combined SJC& POM, except for Sandbar Willow (SW) that showed a negative effect (Figure A4b). Additionally, MF and BE demonstrated the lowest CV values. See appendix A5 for estimates and relationships with CV.

Similar to the relative SWP model, the mixed effects model, incorporating random effects of Year and Season, was applied to the relative CV change dataset. As with SWP, the analysis yielded a notably low performance, with an R2 value of 0.013. Consequently, due to its limited explanatory power, this analysis was excluded from the overall assessment.

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Figure A4b: CV as a function of combined Q from SJCand POM per species (AW; Arroyo Willow, BE; Blue Elderberry, BW; Black Willow, MF; Mule Fat, SW; Sandbar Willow, SY; California Sycamore).

Table A4: Mixed effects model performance and significance for canopy volume

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| *Rsq* | *ICC* | *Fixed Effect Predictor* | *Significance* | *Relationship* |
| 0.23 | 0.18 | Q | No | - |
| SJC& POM combined | Slight | Increase in CV with increase in Q (depending on species) |
| Replacement | Yes | Increased CV in replaced trees |
| Year | Yes | Reduces with year |
| Group | Yes | Variable: highest in group 3 and 1 |
| DistanceToSJC002 | Yes | Negative relationship |
| Substrate | Yes | Varied: CV lower in Bedrock |
| Tree Position | Yes | CV lower in Medium |
| Season | Yes | CV higher in Spring |
| Damage to Tree | Yes | CV lower in damaged trees |
|  | ***Random Effect Predictor*** |  |  |
| 0.18 | Species | NA | Lower in Mule Fat and Blue Elderberry |

### Predictive modelling

#### Probability of increased stress

The logistic regression analysis conducted for CV demonstrated notably poor performance overall, yielding an R-squared value of 0.005, indicative of weak predictive capability (Figure A4c). While three individual predictions (Arroyo Willow: 0.03, Sandbar Willow: 0.09, Mule Fat: 0.03) exhibited slightly better performance than the aggregate model, these species still displayed limited predictive power, with some predicted relationship effects diverging unexpectedly (Figure A4d). Consequently, the predictive utility of these models for CV remains unreliable, and it is not possible to use the predictions for CV at this time.

A diagram of a different discharge

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Figure A4c: probability of increased CV stress due to outfall discharge. Grey dashed line is the baseline discharge from years 2018-2020, red area is the median current combined discharge from years 2021-2022. Green dashed lines are the median delta combined discharge from 2021-2022 for fall and spring.

A graph showing different colored lines

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Figure A4d: Probability of CV stress as a function of combined discharge (SJC& POM) per species

#### A5: mixed model estimates and relationships

##### Stem Water Potential

A diagram of a number of individuals

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Figure S 1: Mixed effects model estimates for stem water potential

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A graph of a company's value

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A graph with red lines

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A red line graph with numbers

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Figure S 2: Mixed effects model significant relationships of fixed effects with stem water potential, from top to bottom; replacement trees, year, group, distance to SJC, substrate, position of tree.

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Figure S 3: Mixed effect model random effects: top: Seasons, bottom: Species

Canopy Volume

A graph of numbers and a number of individuals

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Figure S 4: Mixed effects model estimates for canopy volume

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A graph showing the value of cv

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A line graph with red dots

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A graph showing a number of values

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A diagram of a graph

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Figure S 5: Mixed effects model significant relationships of fixed effects with canopy cover, from top to bottom; replacement trees, year, group, distance to SJC, substrate, season, position of tree

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Figure S 6: Mixed effect model random effects: Species