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The role of modeling in interpreting monitoring data and refining adaptive management plans in regulated rivers

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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 monitoring outcomes. In this study, 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. We applied modeling techniques to assess the impact of reduced discharge from water reclamation plants on the condition of riparian vegetation. Using stem water potential and canopy volume as indicators of plant stress, we examined their responses to changes in managed discharge over 5 years. 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 significant relationship is likely due to inherent variability within the system, including differences among riparian species and their proximity to the managed discharge and other stressors, which may obscure potential effects of flow reduction. 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 plant 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.

KEYWORDS
ecological modeling, endangered species, flow-ecology, riparian habitat, water reclamation plant (WRP)

Introduction

Adaptive management is a commonly proposed tool to support decision making in the face of uncertain outcomes. Adaptive management is an iterative process in which alternative management actions are evaluated, implemented, and monitored to improve understanding of system responses and inform subsequent management decisions (Walters and Green, 1997). Since its inception, adaptive management has become increasingly necessary as resource management decisions have become more complex and changing climate conditions increase non-stationarity in systems being managed. This is particularly true for aquatic ecosystems, but also applies to other ecological systems, 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.

There are two general approaches to adaptive management. The resilience-experimentalist approach which uses complex ecological models and knowledge gained by experimentation and the decision-theoretic approach which relies on structured decision theory and simpler ecological models. In practice, the decision-theoretic approach is more commonly used because it is thought to be more practical to implement and in theory can lead to decisions in a shorter timeframe (McFadden et al., 2011). Few adaptive management programs have fully achieved their goal of reducing uncertainty through iteratively learning from prior outcomes and hypothesis driven adjustment. Achieving this goal requires adaptive management to be aligned with clearly defined, measurable management objectives and targets that account 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 show measurable responses to flow interventions. This delay can complicate decisions on how to adapt management interventions, increasing the risk and uncertainty associated with achieving desired environmental outcomes (Capon et al., 2018).

Prosser et al. (2021) note that differences between adaptive management theory and practice arise because management decisions unfold over multiple timeframes, from implementation lead time to operational effectiveness and long-term legacy effects. Successful adaptive management programs have allowed 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 pilot projects whose early observations informed the development of a mature adaptive management framework and more ambitious restoration activities (Littles et al., 2022). Similarly, the environmental flow management program from the Terzaghi Dam in British Columbia, Canada led to refinement of their monitoring program after 4 years, including the reduction of non-diagnostic benthic metrics and modifications to sampling methods to reduce uncertainty and improve interpretability 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 improve management outcomes, particularly in older management programs not originally designed to accommodate adaptive management. Effective adaptive management also requires a sound decision-making process, sustained engagement with external stakeholders, and mechanisms to address differing values and risk tolerances under uncertainty (Failing et al., 2013). However, the extended timeframes necessary to inform adaptive management decisions are problematic because 1) regulatory decisions are often required on shorter timeframes, and 2) stakeholder turnover can create 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 can support adaptive management by providing early insight into relationships between management actions and ecological responses, allowing monitoring data to be evaluated within the initial years of program implementation (Irving et al. in review). Linking management actions, environmental covariates, and response measures earlier in the monitoring trajectory modelling helps managers identify key sources of uncertainty and prioritize where enhanced monitoring is needed (Runge et al., 2011). Modeling can also be used to predict the potential ecological outcomes of management interventions, thereby supporting hypothesis driven adaptive management. Collectively, these approaches to modeling can inform timely refinement of management strategies in response to monitoring outcomes and support process documentation that can create a legacy of the decision-making process for managers and 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, United States where modification of discharge of treated wastewater is desired to promote water reuse, without adversely affecting riparian habitat that has historically been occupied by the federally (U.S. Fish and Wildlife Service, 1986) and state (California Endangered Species Act) endangered Least Bell's Vireo (*Vireo bellii pusillus;* LBV), a small, migratory songbird, and sensitive riparian species reliant on the managed wastewater flows. The goal was to use modeling to explore the sensitivity of various indicators to effects of flow modification vs. other stressors, to estimate time frames of response and to provide recommendations for modification of indicators for future monitoring. This project provides important lessons for other adaptive management programs that consider 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 Service, 1986) and state (California Endangered Species Act) endangered Least Bell's Vireo (*Vireo bellii pusillus;* LBV, a small migratory songbird) downstream of the WRP discharge, the

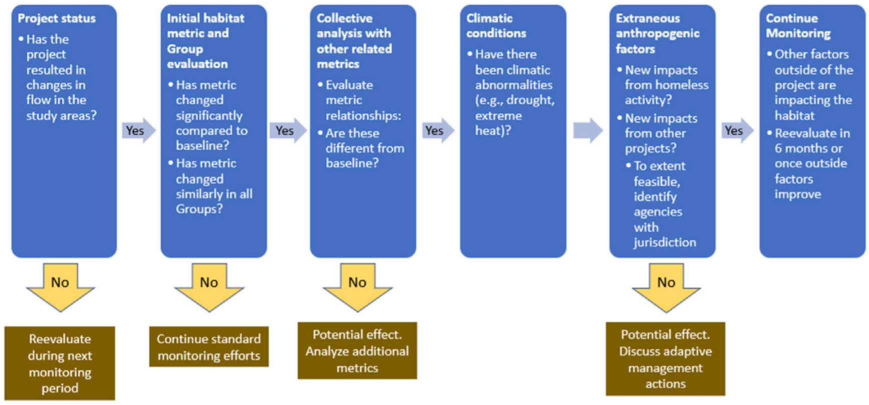

FIGURE 1
Decision process included in the AMP for determining the need for adaptive management measures (Wood, 2020).

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 water reuse project (Wood, 2020). The intent of the AMP is to provide a method of monitoring site conditions (i.e., the monitoring plan) each year to evaluate riparian habitat characteristics for the LBV and to assess whether there have been changes to habitat that would trigger consideration of changes to water management activities, such as increases in flow. The AMP included a set of monitoring objectives and associated “triggers” that if exceeded would indicate the need for adaptive management actions. In addition to riparian vegetation mapping, stem water potential (SWP) is included as an indicator of short-term stress associated with altered flows, while canopy volume (CV) is included as an indicator of more chronic stress on riparian vegetation. The AMP includes a basic decision process for determining when changes in SWP or CV necessitate consideration of implementing adaptive management measures (Figure 1).

The AMP is overseen by an interagency Habitat Management Committee (HMC), which is 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 riparian 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

In practice, it is challenging to determine whether observed changes in habitat are meaningful and if they are related to changes in WRP discharges (flows) vs. other stressors present in the system (e.g., flood control maintenance, sediment management, vandalism). The HMC needed mechanisms to explore potential effects of changes in WRP discharge and inform management decisions in the near term without waiting for a decade or more of monitoring data before determining whether adaptive management was warranted.

Aims and objectives

The primary aim of the study was to apply modelling techniques to assess how WRP discharge, and the supplementary stressors, affect six species of riparian vegetation, by 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 selected for the study have most influence on the stress indicators?
2. How sensitive are stress indicators to the 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 in stress indicators?

Study area and methods

The AMP monitoring plan is focused on portions of the SGR and associated areas that may be affected by changes in the volume

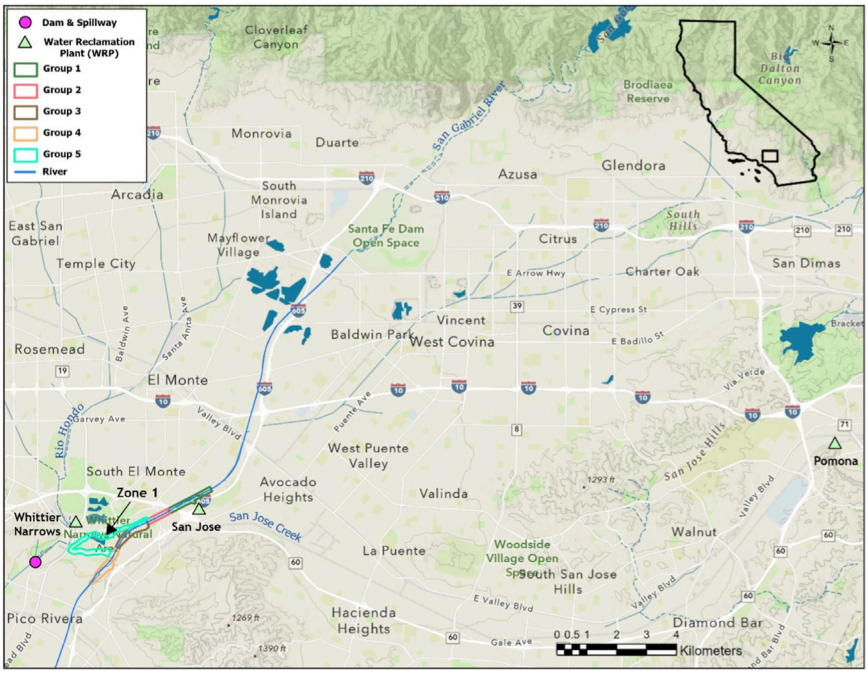

FIGURE 2
Regional map showing the study area, locations of WRP discharges and key waterbodies included in the monitoring program.

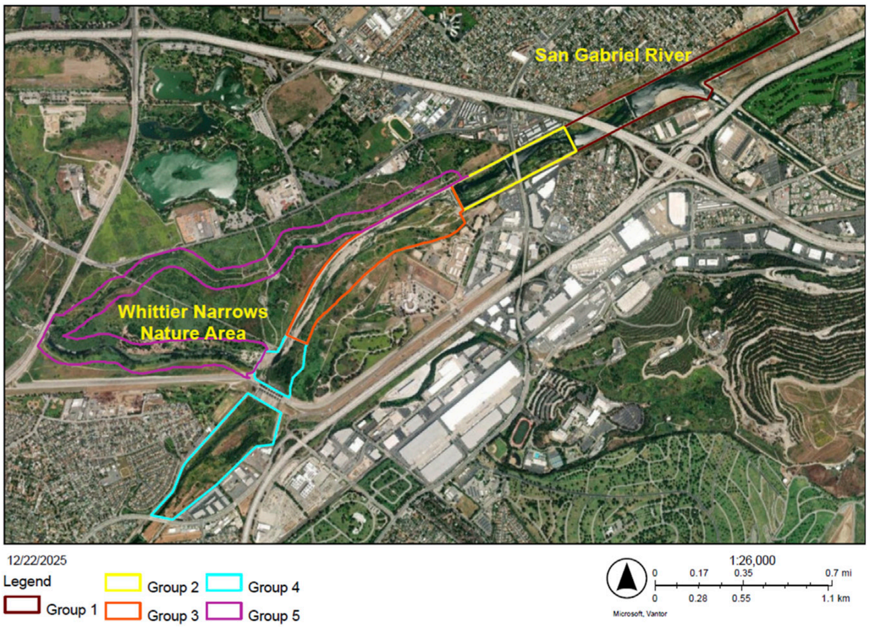

FIGURE 3
Map of project area, with tree groups containing Least Bell's vireo habitat.

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; Figure 2). 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 3), 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 sensitivities to flow conditions. A total of 97 trees were monitored.

The species monitored were Arroyo Willow (*Salix lasiolepis*), Black Willow (*Salix nigra*), Sandbar Willow (*Salix exigua)*, Mule Fat (*Baccharis salicifolia*), Blue Elderberry (*Sambucus cerulea*), California Sycamore (*Platanus racemosa*) and are hereafter referred to as “trees”. Plant species were selected based on 1) native species that commonly occur in the study area 2) species that serve as important habitat elements for the endangered least Bell’s vireo, the ultimate target species of management concern and 3) species that are likely to be affected by changes in discharge and subsequent hydrological conditions.

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. Stem water potential (SWP) is the pressure tension expressed in “atmospheres” required to express a droplet of water from the fresh cut end of a sample leaf. SWP is a proxy for water availability and is considered a proximate indicator of water stress. Its value is that it responds relatively quickly when the tension exceeds the ability of the plant to transpire leading to cavitation and wilting. The disadvantage is that SWP can be influenced by local factors that may not be indicative of long-term plant stress. Canopy volume (CV) estimates the percentage of the live canopy in the sampled individual plant. Canopy volume is considered an indicator of chronic water stress because canopy dieback may result from drought at any time during the growing season. Its value is that it is a more integrative measure of water stress. The disadvantage is that it takes longer to respond and can be influenced by normal senescence or insect injury. CV is also a more subjective measure than SWP, and, as such, strict adherence to measurement methods is essential to obtaining reliable results. Together SWP and CV provide complementary measures of water stress. In addition to SWP and CV, several other climatic and physical factors (Table 1) that may affect SWP and CV were routinely measured.

An annual analysis of the monitoring data from two monitoring events per year evaluate changes to SWP and CV and whether a trigger value has been met that may initiate an increase in water delivery back to baseline hydrological conditions. The trigger value is determined as a significant ($p < 0.1$) decline in the condition of a group or species based on standard paired (baseline with current) t tests. 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 4) 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 3 years of baseline data collection (2018–2020, noting that only the Fall season was monitored in 2018), plus 2 years of effects monitoring (2021–2022) following reduced WRP discharge in 2020. Wet and dry years were defined as above or below project area average of 380 mm of rainfall, respectively. The baseline dataset contained one wet (404 mm) and one dry (308 mm) year, whereas both years in the post-reduction dataset were dry years (2021 = 145 mm, 2022 = 302 mm). 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.

Stress indicators

The 97 trees that are components of Least Bell’s vireo habitat were monitored for two stressor indicators[1]. Stem water potential (SWP) is the pressure tension expressed in atmosphere (atm) 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 of vegetation, 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.

SWP samples were collected in two main steps. First individual leaves or leaf clusters were selected from each tree or shrub. At each plant, a single leaf or leaf cluster was chosen from the shaded portion of the canopy from a location that could be readily accessed. Selected leaves were enclosed in Prune Stem Water Potential Bags (PMS Instrument Company, Albany OR, United States) for a minimum of 30 min prior to measurement. All measurements were conducted between 12p.m. and 3p.m. local time. After the minimum 30 min, SWP was measured using a pressure chamber (PMS Pump-up Chamber, PMS Instrument Company, Albany OR, United States). The instrument was prepared in accordance with the manufacturer instructions. The leaf or cluster was cut and immediately placed into the pressure chamber, with care taken to ensure that a sufficient length of the petiole or twig extended through the chamber lid aperture to allow clear observation. Chamber pressure was then gradually increased until water was observed emerging from the cut base of the leaf, at which point the applied pressure was recorded as stem water potential.

Canopy volume (CV) was visually estimated as the percentage of live canopy in the sampled individual plant. Canopy dieback may result from drought at 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. A minimum of two observers independently assessed canopy volume for each individual tree or shrub, after which estimates were compared and reconciled. In cases of disagreement, a third observer reviewed the assessments and determined the final estimate following discussion of differing observations.

1 Values for Stem Water Potential and Canopy Volume available in Supplementary Table S1.

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 and POM	Monthly (MGD)	Combined discharge from San Jose Creek and Pomona WRPs	Monitoring data	SWP, CV
Discharge: SJC, POM, and 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 (mm)	Observed Precipitation	Monitoring data	SWP, CV
TempMeanModF	Monthly mean (degrees F)	Air temperature	PRISM	Not used

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 year's corresponding to the monitoring data for the Whittier Narrows area (800 m × 800 m grid).

The discharge measured from gages (Q) and WRP Q (single and combined outfalls) was allocated to groups as outlined in Figure 4. The amount of flow received by group 5 was not measured because this downstream area receives flow from several sources that discharge unpredictably based on water diversion operations,

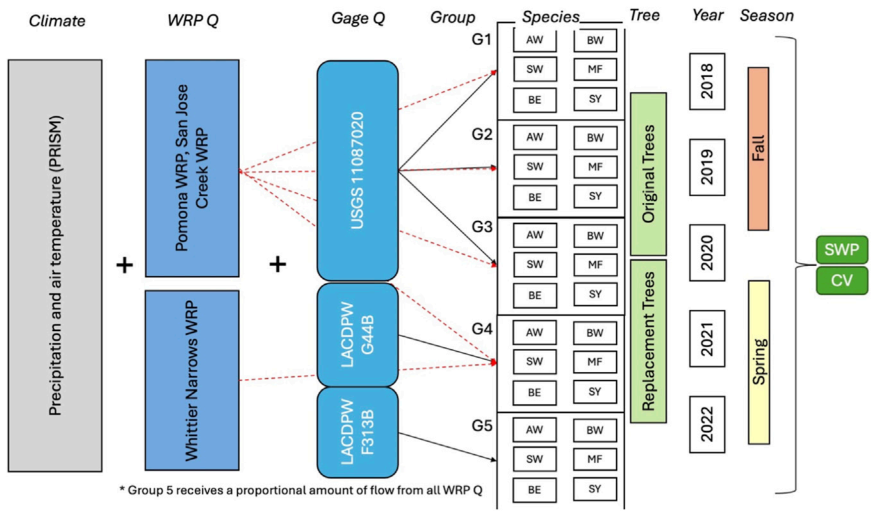

FIGURE 4
Structure of monitoring data. Species - AW; Arroyo Willow, BW; Black Willow, SW; Sandbar Willow, MF; Mule Fat, BE; Blue Elderberry, SY; California Sycamore. SWP; Stem Water Potential, CV; Canopy Volume. Note that group 5 receives a proportional amount of flow from all WRPs. Replacement trees are added into the monitoring program when original trees are destroyed due to vandalism, flood control maintenance, or other unforeseen events. See methods for details.

making reliable flow estimates impractical. Therefore, to retain its inclusion, a constant value of 0.01 cfs was allocated. We conducted a sensitivity analysis on various static and proportional flow values, leading to the conclusion that 0.01 cfs was appropriate for application (see Supplementary 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 Supplementary Appendix A2). The analysis therefore reflected the full extent of available monitoring data, including tree losses over time.

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 missing values were present in Substrate (n = 504), Rainfall Intensity (n = 330) and Distance to SJC 002 (n = 1,536). The first two were missing due to gaps in the monitoring data, while the third reflects replacement trees for which the original coordinates were not available.

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 Supplementary Appendix A3).

Modelling approach

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 (Table 2). 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 in the monitoring program to increase sensitivity to stress-induced changes. All analysis was conducted in R Statistical Programming version 4.4.1 (R Core Team, 2024).

Explanatory model approaches

Random forest model approach

A Random Forest model (RF) is a machine learning technique based on decision trees (Breiman, 2001; Liaw and Wiener, 2002), well-suited for handling complex ecological datasets (Simon et al., 2023; Pichler and Hartig, 2023). They are non-parametric in nature, so they are apt at finding connections between predictors and response variables. However, they do not identify mechanistic

TABLE 2 Assessment questions developed by the Habitat Management Committee and the associated modeling approach used to address the question.

Question	Model approach
Which stressors have the most influence on the stress indicators?	Random forest
How sensitive are stress indicators to physical parameters?	Mixed effects Model
How much stress can be explained by WRP flow?	Predictive logistic regression
How much additional monitoring is needed to detect a change?	Power analysis

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 and Murphy, 2018; Liaw and Wiener, 2002) on the full dataset of 9,588 points.

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) (see Guyon and Elisseeff, 2003). 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. Two variables (Month and TempMeanModF) were removed following this process for both SWP and CV. The final column of Table 1 outlines the predictors used 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 the average squared difference between observed and predicted values, expressed as the square of the response variable with lower values indicating better performance.

The RF algorithm inherently includes an internal validation procedure (out-of-bag error, see Breiman, 2001), 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 4), we performed a mixed effect model (Zuur et al., 2009). 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 stressors 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 and POM discharge correlated with SJC; r = 0.98, and combined SJC, POM and 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, Nakagawa et al., 2017) 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 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 do not appear in both time frames, were excluded (remaining trees; n = 67).

Baseline discharge values were determined as the median discharge observed during the years 2018–2020, 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 and 2022). Wet and dry years were defined as above or below project area average of 379.5 mm 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 R^2 (McFadden, 1979) was applied, which serves as a pseudo R^2 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 Pearson's 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) 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 (Cohen, 1988), comparing stress indicators from before the project's implementation (in 2020) to the most recent complete year (2022). As this analysis compared indicators 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 due to the natural variability caused by factors such as season, species and interannual differences. 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 and Mai, 2023).

Results

To illustrate the process of applying modelling techniques to aid AMP decision making, we show results for SWP and CV.

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 atm^2. Notably, the five most influential predictors for model performance in this analysis were Species, Season, Year, Distance to San Jose Creek (SJC) and Group (Figure 5). 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) atm, which provides additional evidence of the model's effectiveness and reliability.

The mixed effects model also exhibited strong performance as indicated by an R-squared value of 0.65 (Table 3). In this model, two

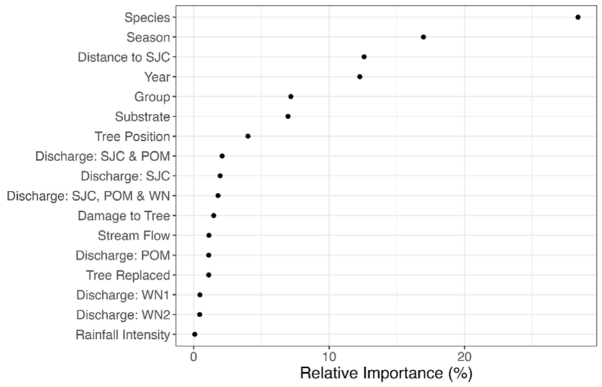

FIGURE 5
Relative importance for stem water potential l (SWP) predictors in the reduced model. Abbreviations; SJC, San Jose Creek; POM, Pomona; WN, Whittier Narrows.

random effects of Species and Season were employed. All random effects combined explained 63% (ICC; 0.63, Table 3) of the model variation; Species alone explained 44% (0.44, Table 3) of the variation. Hence, species accounts for most (but not all) of the random effect variance and is therefore a major driver of variation in the response. Because species explained such a substantial proportion of the variation, it was important to examine the species-specific relationships in more detail. SWP displayed a consistent relationship across all species in response to combined SJC and POM (except for Blue Elderberry (BE), which showed a positive relationship) with Mule Fat (MF) demonstrating the highest SWP values (Figure 6). See Supplementary Appendix A4 for estimates and relationships with SWP. While several predictors displayed highly significant relationships with SWP, i.e., <0.001 (Table 3), 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 5). Distance from SJC did not show statistical significance.

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 7) 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.

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 4). In this model, a single random effect related to Species was employed. While several predictors displayed significant relationships with CV, it is 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 consistently limited relationship across all species in response to combined SJC& POM, except for Blue Elderberry (BE) that showed a negative effect (Figure 8). Additionally, MF and BE demonstrated the lowest CV values. See Supplementary Appendix A4 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 R^2 value of 0.013. Consequently, due to its limited explanatory power, this analysis was excluded from the overall assessment.

TABLE 3 **Mixed effects model performance and significance for stem water potential. ICC; Intraclass Correlation Coefficient, Rsq; R-Squared, SWP: Stem Water Potential, SJC; San Juan Creek, POM; Pomona. Significance based on p < 0.05.**

Rsq	ICC	Fixed effect predictor	Significance	Relationship
0.65	0.63	Stream flow	No	-
		Discharge: SJC and 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
Rsq	**ICC**	**Random effect predictor**	**Significance**	**Relationship**
	0.44	Species	NA	Higher in Mule Fat
	0.19	Season	NA	Higher in fall

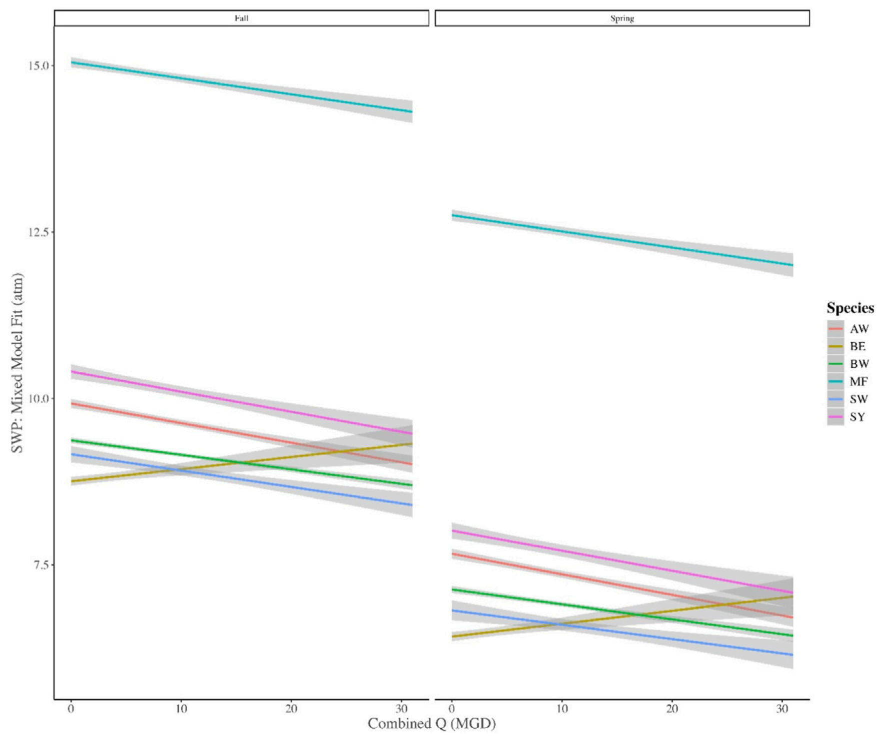

FIGURE 6
SWP as a function of combined flow from SJC and POM by species (AW; Arroyo Willow, BE; Blue Elderberry, BW; Black Willow, MF; Mule Fat, SW; Sandbar Willow, SY; California Sycamore). Flow (Q) is in million gallons per day (MGD).

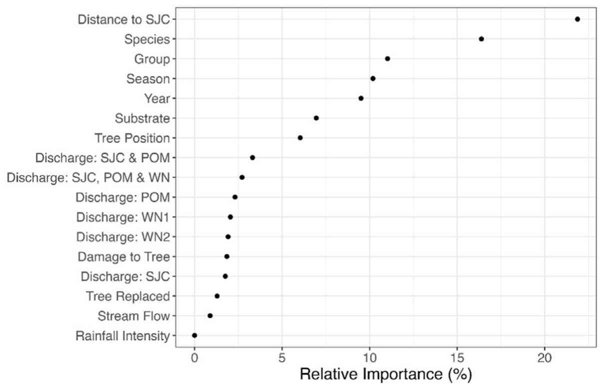

FIGURE 7
Relative importance for canopy volume (CV) predictors in the reduced model. Abbreviations; SJC, San Jose Creek; POM, Pomona; WN, Whittier Narrows.

Predictive modelling

Probability of increased stress

The outfall discharge metric applied in this analysis was the combined SJC and 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 R^2 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 9). 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, reflected in the absence of significance in the RF and mixed model. Consequently, one potential 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.

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 145.3 mm, and 301.5 mm in 2022 (Wood, 2022). Although 2022 was wetter than 2021, the probability of stress is lower for a similar reduction in flow (Figure 9). Model performance for both years was low (2022; 0.05, 2021; 0.07).

TABLE 4 Mixed effects model performance and significance for canopy volume. CV: Canopy Volume, SJC; San Juan Creek, POM; Pomona. Significance based on $p < 0.05$.

Rsq	ICC	Fixed effect predictor	Significance	Relationship
0.23	0.18	Q	No	-
		SJC& POM combined	Yes	No effect or decrease in CV with increase in Q
		Replacement	Yes	Increased CV in replaced trees
		Year	Yes	Reduces with year
		Group	Yes	Variable: Highest in group 3 and 1
		DistanceToSJC	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
Rsq	**ICC**	**Random effect predictor**	**Significance**	**Relationship**
	0.18	Species	NA	CV lower in Mule Fat and Blue Elderberry

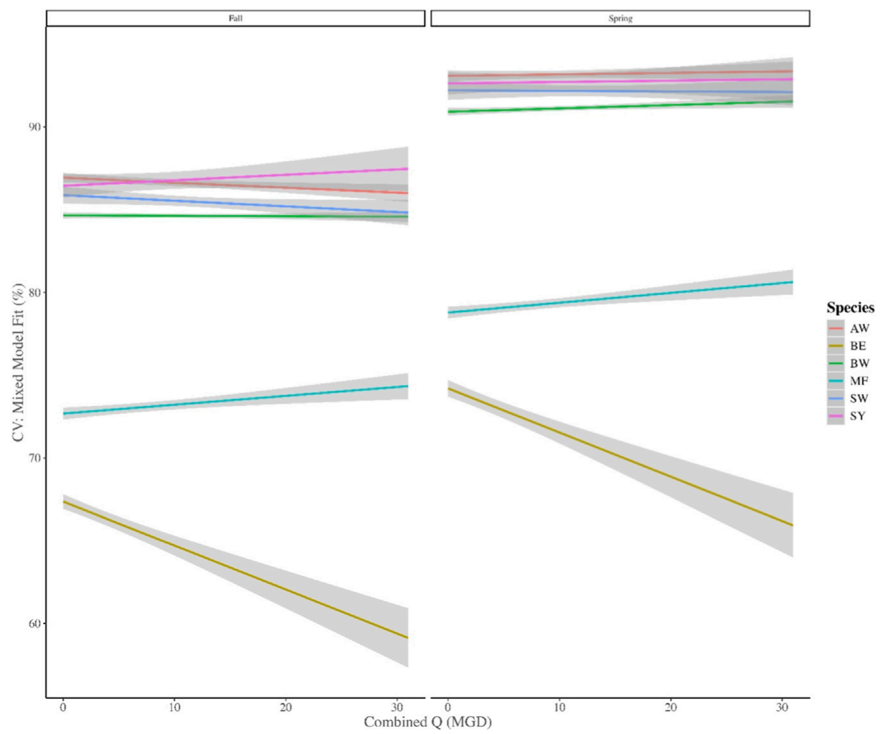

FIGURE 8
Canopy Volume (CV) as a function of combined Q from SJ Cand POM per species (AW; Arroyo Willow, BE; Blue Elderberry, BW; Black Willow, MF; Mule Fat, SW; Sandbar Willow, SY; California Sycamore). Flow (Q) is in million gallons per day (MGD).

The probability of stress predicted per species for SWP performed especially well for California Sycamore (SY, Figure 10), yielding a Nagelkerke R^2 of 0.52. Blue Elderberry (BE), Black Willow (BW) and Mule Fat (MF) performed better than the overall model, however performance remained relatively low ($R^{2:}$ 0.13–0.16). These findings suggest that some riparian taxa may be more sensitive indicators of flow alteration than others.

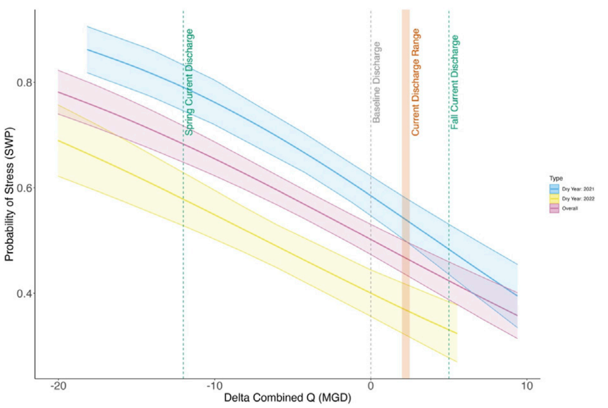

FIGURE 9
probability of increased SWP stress, overall and in dry years due to outfall discharge. Grey dashed line is the baseline discharge from years 2018–2020, red area is the median current combined discharge from years 2021–2022. Green dashed lines are the median delta combined discharge from 2021–2022 for fall and spring. Flow (Q) is in million gallons per day (MGD).

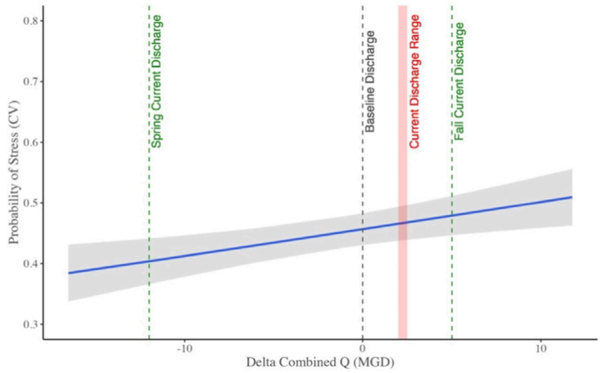

FIGURE 11
Probability of increased CV stress due to outfall discharge. Grey dashed line is the baseline discharge from years 2018–2020, red area is the median current combined discharge from years 2021–2022. Green dashed lines are the median delta combined discharge from 2021–2022 for fall and spring. Flow (Q) is in million gallons per day (MGD).

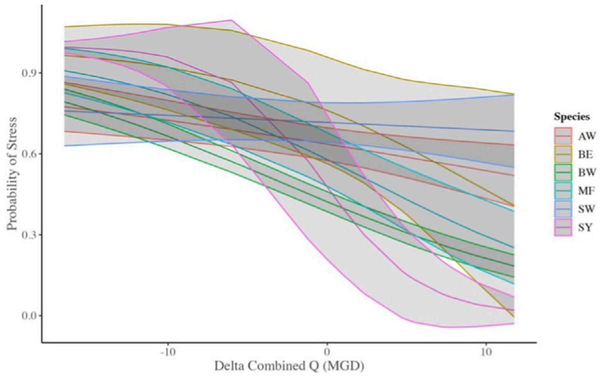

FIGURE 10
Probability of SWP stress as a function of combined discharge (SJC and POM) per species (AW; Arroyo Willow, BE; Blue Elderberry, BW; Black Willow, MF; Mule Fat, SW; Sandbar Willow, SY; California Sycamore). Flow (Q) is in million gallons per day (MGD).

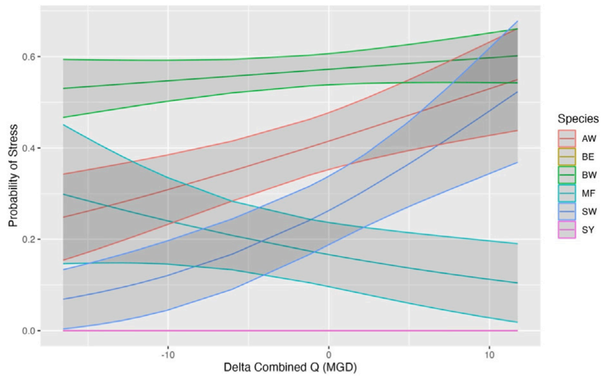

FIGURE 12
Probability of CV stress as a function of combined discharge (SJC& POM) per species. Flow (Q) is in million gallons per day (MGD).

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 11). 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 12). 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.

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 13). 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.

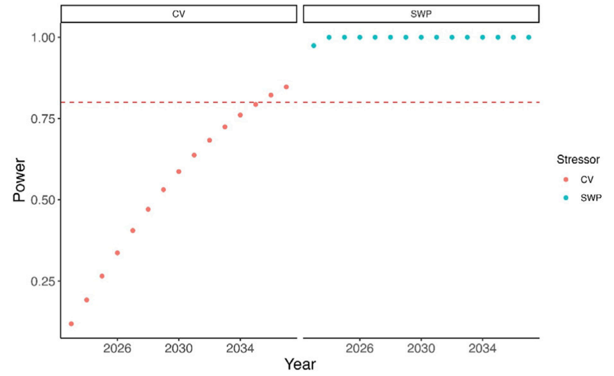

FIGURE 13
Statistical power analysis for CV and SWP in relation to delta Q measured from gages. Red dashed lines indicate the standard statistical power value of 0.8 and corresponding year of monitoring, based on the current sample size (n = 67 trees per season, i.e., 134 trees per year).

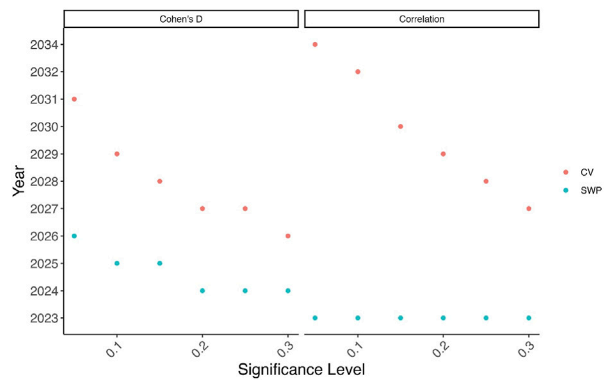

FIGURE 14
Sensitivity of significance levels though the Cohen's D approach (n = 97 trees per season, 192 trees per year) and correlation coefficient approach (n = 67 trees per season, 134 trees per year) applied on delta flow values. Year refers to the first year, the significance level is expected to be reached with additional monitoring (2 seasonal surveys per year).

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.

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 14). For SWP, all significance levels are achievable by 2023 (Figure 14). The Cohen's D approach (Figure 14) indicates that an additional 4 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 4-year timeframe.

Discussion

We applied a combination of statistical models to assess how reductions in discharge from the WRP may influence the condition of 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, as indicated by the predictive and power analyses. However, reduced flow was not statistically significant in the explanatory models, with only weak evidence of a directional relationship in the predictive model as it showed low performance. Instead, Year, Season, Species accounted for the majority of the variation in the data. CV is an integrative measure of plant condition that typically responds more slowly to environmental change than physiological indicators such as SWP. As such, increases in water availability would be expected to support greater canopy development over longer timescales, and empirical studies have shown declines in CV under reduced water availability in riparian systems (Thaxton et al., 2024). The absence of a clear relationship between discharge and CV in this study likely reflects the relatively short monitoring period and high background variability, rather than a lack of ecological linkage between water availability and canopy condition. SWP is an established indicator of water stress initially used to monitor the health of orchard trees (Ortuño et al., 2006). Water potential measurements have also been taken for cottonwood/willow habitats in the American southwest and have been used to provide an indication of species health, as well as for conditions of stress (Williams and Cooper, 2005). Although SWP is a good indicator of water stress, specific responses are often difficult to discern. Multiple stressors often interact with natural climatic patterns to produce complex and sometimes counter intuitive responses in plant growth and survival (Stella and Bendix, 2019). Our findings suggest that variation associated with species, temporal factors, and site characteristics may have influenced the observed patterns, making it difficult to isolate the individual effects of flow modification. Similar confounding factors were observed in a large management study in the lower Mississippi River where drought impacts were masked by effects of land management practices (Wang et al., 2025).

By employing modeling early in the AMP process, we were able to refine the monitoring process. After just 5 years of monitoring, involving three baseline years and 2 years post-discharge reduction, modeling enabled us to adjust the AMP by allowing data interpretation and refinement of adaptive process to occur sooner than would 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 running 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.,

TABLE 5 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 relatively low influence relative seasonal effects	Flow related variables show low to moderate importance	Flow has moderate effect on plant stress, but the inherent variability in system is most influential in the 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

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 5).

First, we were able to identify that SWP was the most responsive stressor indicator monitored during this study, making it a useful early indicator of plant stress. The discrepancy in sensitivity is likely attributable to SWP's responsiveness to shorter time frames of water stress, whereas CV may require more time to reveal observable effects of water stress on riparian species. Nonetheless, both indicators informed adaptative management, as focusing on the most responsive indicator can enable early detection of ecological impacts. In addition, the analysis highlighted species-specific differences in stress (i.e., California Sycamore), which supports the use of targeted indicators rather than reliance on aggregated community responses.

Second, we were able to demonstrate and understand system variability, which led to improvements in the monitoring plan, such as refinement of monitoring locations and seasons, adjustment of protocols, and elimination of some indicators (discussed below). Variables associated with the monitoring design (Species, Group), site characteristics (Substrate, Tree position), and temporal factors (Year, Season) explained the most variation in stress measurements. Climate-related factors (such as rainfall depth and temperature) and WRP discharge had little influence on plant stress, indicating that inherent system variability and non-flow-related factors were 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 have obscured 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. In addition, baseline conditions included both dry and wet years, whereas post-reduction monitoring captured only dry years, which may have confounded water-year type effects with changes in discharge, potentially masking a discharge change signal in the models. Further monitoring that includes both wet and dry years should help clarify these effects.

Third, we were able to inform resource allocation by highlighting that Group 5 contributed little to understanding flow-related impacts. Reliable flow measurements were not available for Group 5 given that discharge into this area occurs via numerous sources in unpredictable ways (e.g., diversions from impounded areas, dam releases, WRP discharges). Recognizing this issue, the HMC considered 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

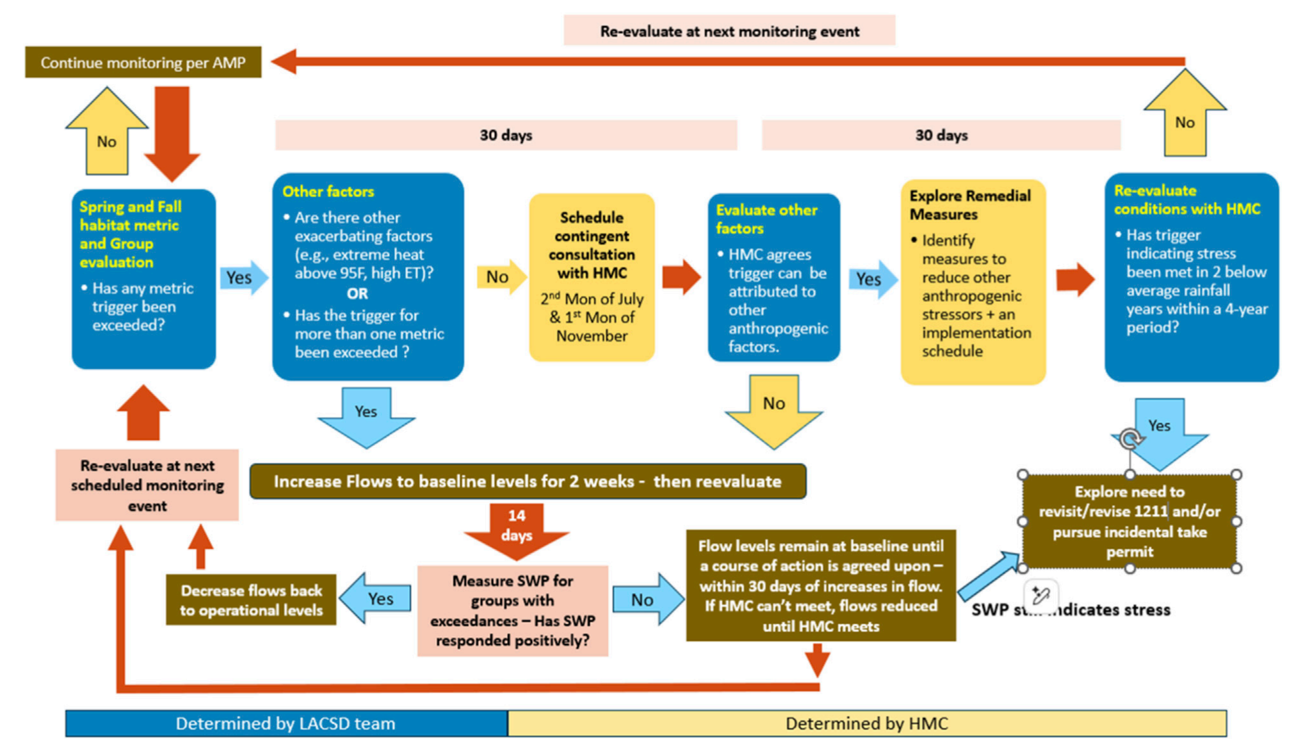

FIGURE 15
Evolution of the AMP decision making process based on outcomes of the adaptive modeling analysis with key findings from previous monitoring events and natural changes to the habitat over time. NB. 1,211 refers to the wastewater change petition under which the permit to reduce flow was issued.

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 15). 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 (e.g., adjustments in timing, increasing replication). Ultimately, the decision matrix should allow the HMC to more readily 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 and the effects of other stressors (e.g., vandalism, flood control maintenance) could obscure the potential impacts of flow reduction. Based on these understandings, 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 among those selected for this study, 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. While these findings highlight important limitations in the current monitoring framework, they also reflect constraints in the available dataset and modelling approaches, which limit their ability to isolate flow effects from other co-occurring stressors.

Assumptions and caveats

While many of the findings of this study highlight limitations in the existing monitoring design and adaptive management framework, it is also important to distinguish limitations associated with the study itself, including constraints in the available data and modelling approaches. First, some key physical factors influencing plant stress, such as soil moisture and depth to groundwater, not included in the monitoring plan may play a more significant role in driving plant stress compared to the surface water parameters collected. In particular, shallow groundwater monitoring was not possible due to the engineered substrate of the study area and the frequent disturbances associated with flood control maintenance activities. 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 and utility. Finally, the power of the models was reduced by gaps in the monitoring data associated with habitat damage not associated with the water re-use project (e.g., fires caused by transient populations).

Wider implications

A more variable climate means that environmental changes, including changes to river flows, may occur more rapidly and conventional (potentially slow) adaptive monitoring and management 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 the 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 human 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 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 documented clearly and consistently to ensure that future staff and stakeholder groups understand and have 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 help 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).

Modeling analysis revealed the shortcomings of attempting to make adaptive management decisions based on evaluation relative to process shown in Figure 1. The simple binary approach to determining effects neglects consideration of multiple co-occurring stressors, most of which are unrelated to changes in WRP discharge. Instead, a multi-parameter, multi dimension decision process is necessary to provide a defensible process for deciding when to increase WRP discharges, thereby reducing water reuse. Figure 15 demonstrates how the decision-making process for the AMP gained clarity (and complexity) based on improved understanding that resulted from the modeling. The updated process allows for consideration of multiple lines of evidence and provide a process for incrementally increasing flow and re-evaluating the effect before committing to long-term management changes. In this manner, environmental flows and water reuse needs can be more effectively balanced and managed over time.

Conclusion

Modeling supported interpretation of early monitoring results and helped refine the adaptive management process in this study. Specifically, the analyses identified stem water potential (SWP) as a more sensitive indicator than canopy volume (CV), with greater potential to detect flow-related effects over shorter timescales. However, the lack of statistically significant relationships between discharge and stress indicators, and the strong influence of species, season, and site conditions, highlighted the dominant role of inherent system variability. These findings provide earlier insight into indicators that provide sufficient sensitivity vs. those that do not and highlight opportunities where early increases in monitoring frequency or intensity can increase the ability to draw defensible conclusions sooner. In turn, this allows for earlier intervention and adjustment to improve effectiveness of monitoring programs and subsequent management decisions. For example, increasing the number of trees sampled may enable responses to water stress and other factors be detected sooner. Monitoring Least Bell's vireo would provide the ability to directly evaluate effects of changes in discharge and provide an opportunity to explore relationships between indicators and species occurrence. The findings of the study also suggest that managing other stressors may be equally important to managing discharge to meet long-term habitat protection goals.

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. Future adaptive management efforts could be improved by incorporating modeling from the onset of the AMP development process. Modeling will provide insight into which indicators are likely to be most sensitive to detecting effects of management actions, to bound expected uncertainty, and to estimate the time frames necessary to detect significant changes. This in turn can help to inform when in the process adaptive measures should be considered. Finally, modeling can be used to explore the likely effect of adaptive interventions to determine the degree to which they may help ensure the management targets are achieved. An integrated monitoring-modeling workflow will ultimately result in more effective and efficient monitoring that is able to support AMP decisions and provide more certainty in actions aimed at improving management success.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

KI: Writing – review and editing, Data curation, Writing – original draft, Investigation, Conceptualization, Formal Analysis. ES: Project administration, Validation, Writing – review and editing, Methodology, Conceptualization, Writing – original draft, Funding acquisition. SC: Visualization, Data curation, Validation, Writing – review and editing, Methodology, Investigation. MC: Investigation, Formal Analysis, Writing – review and editing, Visualization, Writing – original draft. MH: Writing – review and editing, Project administration, Data curation. PH: Project administration, Data curation, Writing – review and editing. ZE: Methodology, Writing – review and editing, Project administration, Validation.

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Conflict of interest

Authors SC and MC were employed by WSP USA Environment and Infrastructure, Inc.

The remaining author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

The author ES declared that they were an editorial board member of Frontiers at the time of submission. This had no impact on the peer review process and the final decision.

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Supplementary material

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