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Evaluation of Human and Ecological Water Management Tradeoffs in a Seasonal Watershed with Spatially-Distributed Demands

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EVALUATION OF HUMAN AND ECOLOGICAL WATER MANAGEMENT TRADEOFFS IN A SEASONAL WATERSHED WITH SPATIALLY-DISTRIBUTED DEMANDS

by

Jesse Lee Rowles

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Approved:

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ABSTRACT

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by

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Utah State University, 2021

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Department: Civil and Environmental Engineering

River managers must balance the needs of the ecosystems that rely on the river by leaving water instream, often while facing demands from human diversions. It is especially difficult to balance these water needs in systems that are highly seasonal and have no instream storage (e.g., reservoirs) since the amount of water instream is completely determined by the climate. An example of a watershed that has both of these characteristics is the South Fork Eel River in coastal northern California. In order to evaluate tradeoffs between human and ecological demands in this system, a water allocation model with water management scenarios and environmental flow requirement scenarios was developed in collaboration with stakeholders and decision-makers. The water allocation model is capable of considering permitted water diversions, as well as unpermitted diversions, which contribute to a significant proportion of water used in forested California watersheds. In total, 11 different human water demand scenarios and 14 different environmental flow requirement ecological demand scenarios were evaluated to identify tradeoffs and facilitate management efforts. To aid in decision making processes, an interactive GUI is also being collaboratively developed to provide visualizations and performance metrics of model results. Then, the results of the water allocation model were assessed based on the characteristics of each location in the model, called reach setting parameters. The performance of water allocation at each location was compared to the value of different reach setting parameters to determine if trends can be found.

(128 pages)

PUBLIC ABSTRACT

Evaluation of Human and Ecological Water Management Tradeoffs in A Seasonal Watershed with Spatially-Distributed Demands

Jesse Lee Rowles

River managers must balance the needs of the ecosystems that rely on the river by leaving water instream, often while also considering human demands. It is especially difficult to balance these water needs in systems that are highly seasonal and have no instream storage (e.g., reservoirs) since water cannot be stored for use throughout the year. An example of a watershed that has both of these characteristics is the South Fork Eel River in coastal northern California. In order to evaluate tradeoffs between human and ecological demands in this system, a water allocation model with water management scenarios and environmental flow requirement scenarios was developed in collaboration with stakeholders and decision-makers to balance the needs of the ecosystem and humans. The water allocation model is capable of considering permitted water diversions, as well as unpermitted diversions, particularly pertaining to cannabis cultivation, which contribute to a significant proportion of water used in forested California watersheds. In total, 11 different human water demand scenarios and 14 different environmental flow requirement ecological demand scenarios were evaluated to identify sensitivity of different parameters and facilitate management efforts. To aid in decision making processes, an interactive GUI is also being collaboratively developed to provide visualizations and performance metrics of model results. Then, the results of the water allocation model were assessed compared to different location-specific characteristics.

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INTRODUCTION

River ecosystems are often a delicate temporal balance of water temperature, hydraulics, and bioenergetics to support native aquatic species' habitat requirements (Webb et al. 2003, Peterson et al., 2001). Native species are typically adapted to hydrologic characteristics that compose natural flow regimes. This adaptation becomes especially important when these flow regimes are highly seasonal. However, human activities in river ecosystems are the primary mechanisms behind unnatural disturbances to natural flow regimes that are commonly stressful for native species and conducive for invasive species (Gasith & Resh, 1999). Therefore, to protect, preserve, and manage aquatic riverine ecosystems, it is essential that rivers be provided with sufficient water to meet minimum ecological thresholds needed by native species at different times of the year. Given that most rivers are also a primary source of freshwater for anthropic activities [e.g., water supply for municipal and agricultural use, hydropower, and flood control (Geist 2011; Postel & Richter 2003)], there are often competing demands that depend on river flows.

Watersheds with Mediterranean flow regimes are particularly challenging for balancing competing water demands due to their extreme seasonality. Mediterranean flow regimes are characterized by very low summer flows and high-flow winters, with 65-80% of annual precipitation occurring in three of the winter months from only a few major storm events (Gasith & Resh, 1999, Power et al. 2015). These flow regimes are also subject to large interannual variability in addition to annual variability. Thus, water managers are faced with the difficult task of making decisions that effectively balance competing in-stream and out-of-stream water needs. These needs become exceedingly important when the native aquatic species are threatened or endangered. In this case, the water needs of these species may be prioritized above human water demands through regulations such as the Federal Endangered Species Act (USFW 1973). Therefore, water resource management is particularly important in these watersheds since the seasonality makes providing water for off-stream human needs difficult, while the critical or endangered nature of the instream native species dictates that necessary precautions are taken to ensure their habitat is provided for (Kondolf et. al 2012).

Watersheds in Northern California epitomize Mediterranean-type watersheds, and are therefore of growing concern due to the numerous and distributed nature of the diversions that occur in support of human water demands. This includes changing legislation concerning cannabis operations and water diversions associated with them. Specifically, cannabis demands are of particular interest due to CA Senate Bill 837 (CA State Government, 2016), which mandates the protection of native ecosystems from negative impacts of cannabis cultivation. Additionally, due to changing legalization of cannabis, there is a mix of permitted and unpermitted cannabis demands across the entire state (Dillis et al. 2019). The different types of cannabis demands have different impacts on instream flows due to the nature of their diversion operations (Miearu et al. 2017). Conflicting water demands are being further exacerbated in this region by declining ecological conditions (NMFS, 2016), increasing human water demands, and extended drought conditions driven by climate change.

This thesis study, funded by the State Water Resources Control Board (SWRCB) of California aims to address all of these concerns. Some previous studies have focused on Northern California and permitted cannabis water demands (Morgan et al. 2020), both permitted and unpermitted cannabis demands (Dillis et al. 2019), and general impact of agricultural demands (including, but not focused on cannabis demands) on environmental flows (Grantham et al. 2019). There have also been studies done to address coupled management of human and environmental demands in small northern California watersheds with no significant reservoir storage, but it is often only performed at a single location at the outlet (e.g., Ta et al. 2016). As far as the authors can tell, no studies have considered the relative impacts of unpermitted and permitted water demands on environmental flows in conjunction with setting instream flow policy across a large watershed with many small, distributed diversions points and varying hydrologic and demand characteristics.

RESEARCH OBJECTIVES AND QUESTIONS

This research presents a novel decision support system framework that evaluates water allocation performance at numerous locations at a daily time step, and allows water managers to evaluate the impacts of different instream flow or water management policies in unregulated watersheds. This was performed in a study watershed in the North Coast region of California, USA which exemplifies unregulated, or lacking of significant instream storage, seasonal conditions with numerous, small, and distributed water demands. A collaborative modeling approach was used to develop the DSS to help water regulatory and environmental agencies evaluate water management alternatives in a complex and ongoing policy process for the study region. My specific research objectives and questions were to:

1. Propose and evaluate alternative scenarios that represent varying amounts of human and ecological flow demands used in a water allocation model.
2. Assist in the development of a dynamic web-based user-interface to aid in visualization and interpretation of water allocation model results and facilitate development of environmental flow prescriptions by watershed managers.
3. Analyze trends in ecological and human water supply performance across the watershed and identify dominant controls on performance and sensitivity using model results.

Specific research questions based on model results include:

[Q1] How does water demand and ecological performance change at different locations based on hydrologic and demand-based characteristics of those locations?

[Q2] (a) How sensitive is performance to changes in human demand characteristics? In general, are there adjustments to human demands that have larger effects on ecological performance than others? (b) Do these relationships between human demands characteristics and performance vary with channel reach settings?

[Q3] How do climate conditions affect water allocation performance at different locations? Alternatively, how does water allocation performance vary with climate conditions?

[Q4] How much does natural climate variability impact performance relative to different amounts of ecological or human water demands?

CASE STUDY

To accomplish these objectives, the South Fork Eel River (SFER) watershed in the North Coast of California was used as a case of study. The SFER is particularly difficult to manage due to its Mediterranean flow regime (CDFW 2014) and lack of instream storage infrastructure such as dams or large instream reservoirs. The SFER is in northern California, USA, and has a drainage area of 689 km^2.

The SFER watershed has significant amounts of both permitted and unpermitted human water demands, primarily for irrigation. The permitted demands are tracked and managed using the electronic Water Rights Information Management System (eWRIMS), which tracks details of each water user's diversion amount over time including the beneficial use, quantity, and source location (Worth 2020). Unpermitted water diversions mostly occur in support of illegal cannabis farm operations. These diversions are of particular interest due to the Senate bill 837 in 2016 (CA State Government, 2016), which tasked environmental agencies in California with determining the negative impacts of cannabis cultivation demands. Both types of water users have peak demands during the dry summer months and are spatially distributed throughout the watershed, with particular prevalence in headwater locations. For example, at the outlet of a sub-watershed within the SFER called Redwood Creek (used in model development, see below), 1.0 and 1.9 cfs of water are permitted for human demands in August and January, respectively. This same location has mean monthly flows of 3.8 and 211.9 cfs in August and January, respectively, as calculated from an unimpaired hydrology model. This means that in the driest month, 26.3% of the unimpaired flow is demanded, while only 0.8% is demanded in the wettest month.

The SFER watershed has been identified as one of five priority watersheds for developing instream flow requirements under the California Water Action Plan (Worth 2014) due to the variety of threatened native salmonids (Yoshiyama et al., 2010). Specifically, the Northern California Coast coho (fall-run), steelhead (winter- and summer-run) and chinook salmon (fall-run) have been identified federally as threatened anadromous species in the watershed under the Endangered Species Act (Moyle et al., 2017; CDFW, 2014). The combination of critical salmonid habitat and heavy human water demands makes this watershed of particular interest to water managers and natural resource agencies. Water management decisions are currently underway in the SFER to protect these species and evaluate the impact of bringing unpermitted irrigators into compliance, making it a prime case study to develop these methodologies for similar systems.

To address the research objectives in this thesis, a water allocation model was used that was recently developed for use in the SFER. This water allocation model is being designed for use throughout the entire SFER, but is currently only completed for 11 locations within the Redwood Creek sub-watershed (Figure 1). These 11 locations were selected based on guidance from the SWRCB to include locations with existing gage stations installed by California Department of Fish & Wildlife (CDFW), Salmonid Restoration Federation (SRF), and SWRCB, as well as one location at the outlet of Redwood Creek as defined by United States Geological

Survey (USGS) delineations of Hydrologic Unit Code (HUC) 12 (Seaber et al., 1994). These locations are a subset of 392 possible locations throughout the SFER watershed.

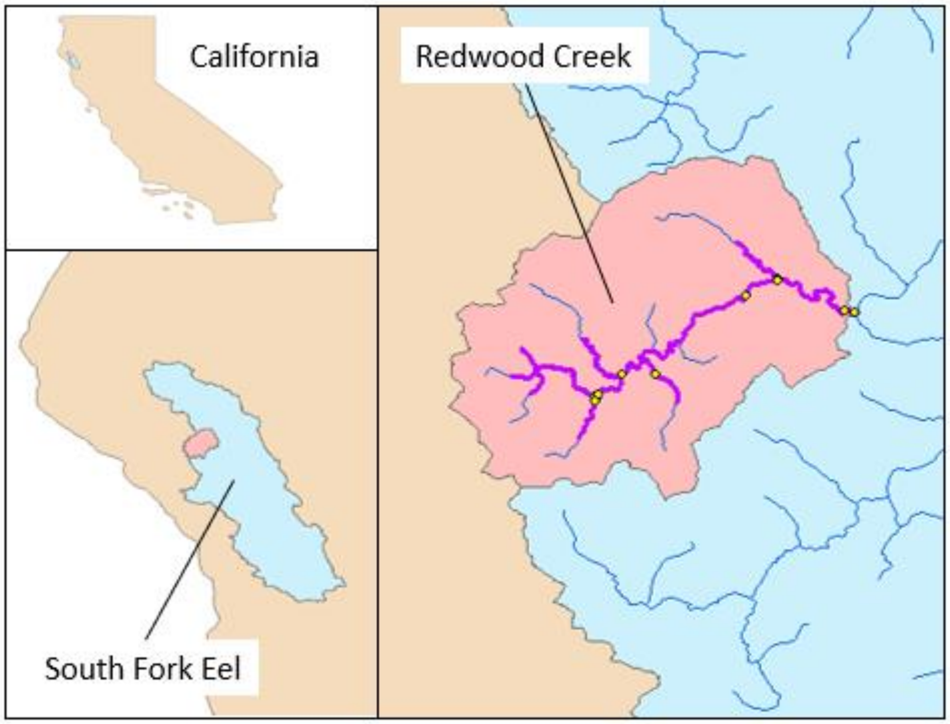


Figure 1-Locations of the SFER watershed and Redwood Creek sub-watershed within California. The water allocation model locations within Redwood Creek are shown as yellow points with reaches defined as the thick magenta lines.

BACKGROUND

Environmental Flows

Sufficient stream flows are critical for preserving river ecosystem health (DeWeber & Peterson, 2020). The presence and movement of water effects physical, chemical, and biological processes that determine the distribution and abundance of aquatic species. Sponseller et al. (2013) classify the ecological roles of water into three mechanisms whereby water acts as: (1) a resource or habitat for organisms; (2) a vector for the exchange and movement of organisms, nutrients, and material by controlling hydrological connectivity (Fullerton et al., 2010); and (3) a driver of disturbance and geomorphology (Horne et al 2017). Therefore, sustainable river management practices should be designed to safeguard local aquatic ecosystems by supporting these mechanisms and maintaining appropriate flows.

There are various approaches or methods to determine how much water is needed in a given location to maintain native aquatic ecosystems. The amount of water to remain instream to provide for these ecosystems over time is referred to in this thesis as instream flow targets (IFTs). This term intends to distinguish the desired target flow from the actual ambient stream-flow that may or may not achieve these targets. The appropriate flow estimation method(s) depend on fundamental understanding of the river and specific management goals such as the desired ecological outcomes, priorities and interest of the involved stakeholders, and available data (Jowett 1997). Two types of general methods for developing IFTs are top-down and bottom-up approaches.

Top-down approaches to develop IFTs are used to capture the natural hydrologic variability – both annually and interannually – based on historic flow data at or near a location or modeled unimpaired flow. These approaches are called top-down since they are based on allowing small portions of flow to be diverted from the full unimpaired flow regimes to holistically support all ecological functions associated with the natural flow regime. The most straightforward top-down approach is a Percent-Of-Flow approach, which simply takes the calculated unimpaired flow for a given day and sets a certain percent of that flow as the IFT. Another approach could consider the key elements of the annual hydrograph at a location that are desired to be preserved (Yarnell et al., 2015, 2019). These approaches are better suited for watersheds without significant reservoir storage than bottom-up approaches (Miearu et al., 2017). They are also advantageous since they only require flow data, whether from a hydrology model or based on historic flow data.

Alternatively, bottom-up IFT approaches focus on a specific ecosystem characteristic to protect and preserve. They are often site-, species-, and life stage-specific (Ghanem et al. 1996), so are especially useful when a specific species at a specific location is desired to be protected. Specifically, water managers may find these approaches favorable when critical or endangered native species are at risk due to changing water management policy or availability of water and when water managers are in danger of being heavily penalized for not doing whatever possible to protect them. Bottom-up approaches are often more data-intensive. There are many bottom-up approaches to develop IFTs that rely on some combination of historic or modeled flow data and process-driven or empirical models describing the relationship between flow and physical habitat variables (e.g. stream temperature, hydraulics) (Sinokrot et al., 2000) or species population dynamics (Poff et al., 2010). One common bottom-up approach is hydraulic habitat suitability modeling, which use hydraulic models and empirically derived habitat suitability curves to identify discharge ranges over which depth and velocity conditions are suitable for specific species or life-stages (Lamaroux et al., 1998; Van Broekhoven et al., 2006; Biggs & Stokseth 1996).

Human Water Demands

Understanding the magnitude and timing of water needed to support current and future human water demands within a system is an essential step in balancing human and ecological water requirements. Human water demands may include irrigation, municipal water supply, and hydropower, among others (Worth 2020). In arid seasonal regions where water is scarce and highly regulated, a single source of permitted human water demand is known as a water right. Some regions maintain electronic water rights databases which not only detail each water right (including the beneficial use, quantity, and source location of each source of water demand), but also the amount of water diverted in each historic month (Worth 2020) like eWRIMS. These tools can provide the amount of water reported to support human demands, which can be different than the amount that is permitted to each water right, making this a powerful tool for more realistic diversion estimation for each water right. This information is not only essential for monitoring and regulating the total amount and timing of legal, or permitted, demands within a watershed, but also to address how historic demands have changed to begin to provide estimates of future demands. Water right management plans are especially important in watersheds without significant reservoir storage since human demands typically require diversion at many locations throughout the watershed rather than at the location of the reservoir. This makes management to support both human and ecological demands a challenge to water managers (Baron et al., 2002).

Particularly in densely forested and sparsely populated regions in northern coastal California, significant unpermitted diversions can occur, usually in support of irrigation for illegal cannabis operations. Bauer et al. (2015) estimated that at least 36% of the annual 7-day minimum stream-flow would be required by illegal cannabis farms in the Salmon Creek (contributing area = 95.1 km^2) watershed of northern California. Due to the unregulated nature of these demands, they occur without consideration for habitat needs or other water management decisions. In other words, these diversions occur to satisfy the full extent of their needed water, even if that means removing all of the water from the river (Bauer et al. 2015). Thus, another challenging consideration for water managers is if these unpermitted diverters should be brought into compliance and, if so, how, including determining available water for new water rights and off-stream storage requirements. Ultimately, in order to obtain a realistic understanding of how much water is available for ecosystem needs after human demands are supplied, all human demands, both permitted and unpermitted, must be considered.

Seasonal Water Storage

The difficulty in managing water demands in Mediterranean flow regimes is intensified by the low-flow summers which have highest irrigation demand. One of the most widely-used water management strategies for addressing the phase lag between water supply and water demand involves the use of water storage. Storage can be implemented as instream storage (generally via dams and other in-channel structures) or off-stream storage (tanks, pumped reservoirs, aquifers, etc.). While systems with water storage capabilities add an additional management challenge, they have the benefit of being able to store excess water from the wet season for use during the dry season or times of drought.

Instream water storage is often accomplished through the use of dams (e.g., 77% of the rivers in the U.S., Canada, Europe, and all former Soviet Union countries are significantly altered by dams [Dynesius and Nilsson 1994]). As a result, the vast majority of studies that evaluate tradeoffs between human and ecological flow needs have focused on systems with significant reservoir storage (e.g., Cardwell et. al 1996, Homa et. al 2005, Null et. al 2012). These studies are of particular interest in the semi-arid western U.S. (Sabater et al., 2011) where an extensive reservoir network has enabled significant urban growth. Systems with substantial surface water storage facilitate integrated water management because reservoir releases can be used to control the amount and timing of water released downstream such that human and ecosystem demands are optimally met (e.g., Downs et. al 1991, Lane et al., 2014, Sandoval et al., 2014). In-stream storage reservoirs are useful because they can store more water compared to off-stream storage methods. They allow water managers to directly control the amount of water instream below them via the use of optimized water release procedures that allow for appropriate amounts of water instream for both ecological and human water demands. These are simpler as well, since all of the water available for the different demands is at a single location, rather than distributed throughout the watershed.

However, not all seasonal watersheds with high demand during the dry season contain reservoir storage to help overcome this misalignment of supply and demand. These systems are of particular interest since they still have human and ecological needs that must be considered year-round, yet do not have a way to regulate the flows within them. Therefore, approaches to water management decision-making in these systems may need to be more innovative than that in systems with reservoir storage (Deitch et al., 2009; Grantham et al., 2010; Mireau et al., 2017). Off-stream water storage is here defined as the process of individual diverters removing water from the stream and moving it to an external location where it can be stored until it is needed. The storage location can be immediately adjacent to the stream or at some distance from it, requiring a method of transport to move the water from the stream to the storage location (Deitch & Dolman 2017). The volume of water that can be stored via off-stream storage is much less than that of instream storage and the use of off-stream water storage techniques requires the additional infrastructure required to remove and store water external to the stream. However, off-stream storage has the benefit of not being limited to a single location and can be implemented without the expensive, time-consuming, and potentially invasive requirement of installing a dam for water storage.

Decision Support Systems (DSS)

A common approach to consider ecological and human water demands in watershed management efforts is to combine data, estimation methods, and computer modeling into a system that can inform management decisions and practices. These are referred to as Decision Support Systems (DSS), which are developed to facilitate water allocation strategies for current and future watershed scenarios, changes in water resources, and uncertainty in amount of water available or demanded (Forni et al., 2016; González et al., 2019; Guo et al., 2014).

DSS for water systems often include a water allocation model, which apply a water balance of inflows, outflows, and system storage in addition to prioritization ranking to determine how much water can be supplied to demand nodes (i.e., water users) at different locations and times (e.g., Ge et al. 2013). The process of developing a water allocation model should directly involve regulatory, academic, and environmental organizations, all with different interests in the system. For example, an organization like California Trout or Trout Unlimited would be more invested in providing flows for native trout habitat while other stakeholders such as individual water rights holders would be more interested in meeting human demands. Therefore, development of a water allocation model that fully considers all the needs of the system should incorporate information and feedback from diverse stakeholders with many perspectives and priorities.

The process of involving multiple stakeholders throughout development of DSS and their accompanying water allocation models is called collaborative modelling (Cardwell et. al, 2011). Hereafter the term ‘stakeholders’ will be used to describe a member of any of the interested parties detailed above. Collaborative modelling often involves stakeholders that represent a variety of interests including environmental organizations, local or state governments, research-based organizations (e.g., universities), or organizations that have substantial water rights in the system. Collaborative modelling not only acknowledges the importance of involving as many stakeholders as possible throughout the process, but also that the process of model development is iterative and changes as results and/or information are produced. It is also likely that the use of collaborative modelling can accelerate development time by removing the ‘bottle neck’ associated with data collection and other phases of development (Basco-Carrera et al., 2017). The versatility and effectiveness of collaborative modelling to support water resources management has been demonstrated in the Connecticut River, Upper Great Lakes, Potomac River, and Rio Grande basin (Cardwell et. al, 2011, Sandoval-Solis et. al, 2013).

METHODS

Watershed DSS

To achieve the project research goals, a large effort was undergone to develop a DSS that consists of three major components: Data Compilation, Water Allocation Model, and Performance Assessment (Figure 2). The goal of the DSS is to provide more information about the availability of water in the SFER in support of environmental and both permitted and unpermitted water demands and about how changing and uncertain estimations of demands and off-stream storage impact this availability. Specifically, the Data Compilation component involves working with stakeholders to compile the data required to run the water allocation model, including the hydrology model used, estimates of permitted and unpermitted demands, and different ways of determining environmental flows. The Water Allocation Model component involved bringing in and processing inputs from the Data Compilation phase to and running the water allocation model. Finally, the Performance Assessment component deals with the processing and visualization of water allocation model results both through a web-based public user-interface, and supplemental analyses outlined in this thesis. Figure 2 presents the overall workflow of the DSS and specific elements of the three components to clarify what was accomplished as a whole and what stakeholders contributed to each part, while highlighting each of my specific research objectives.

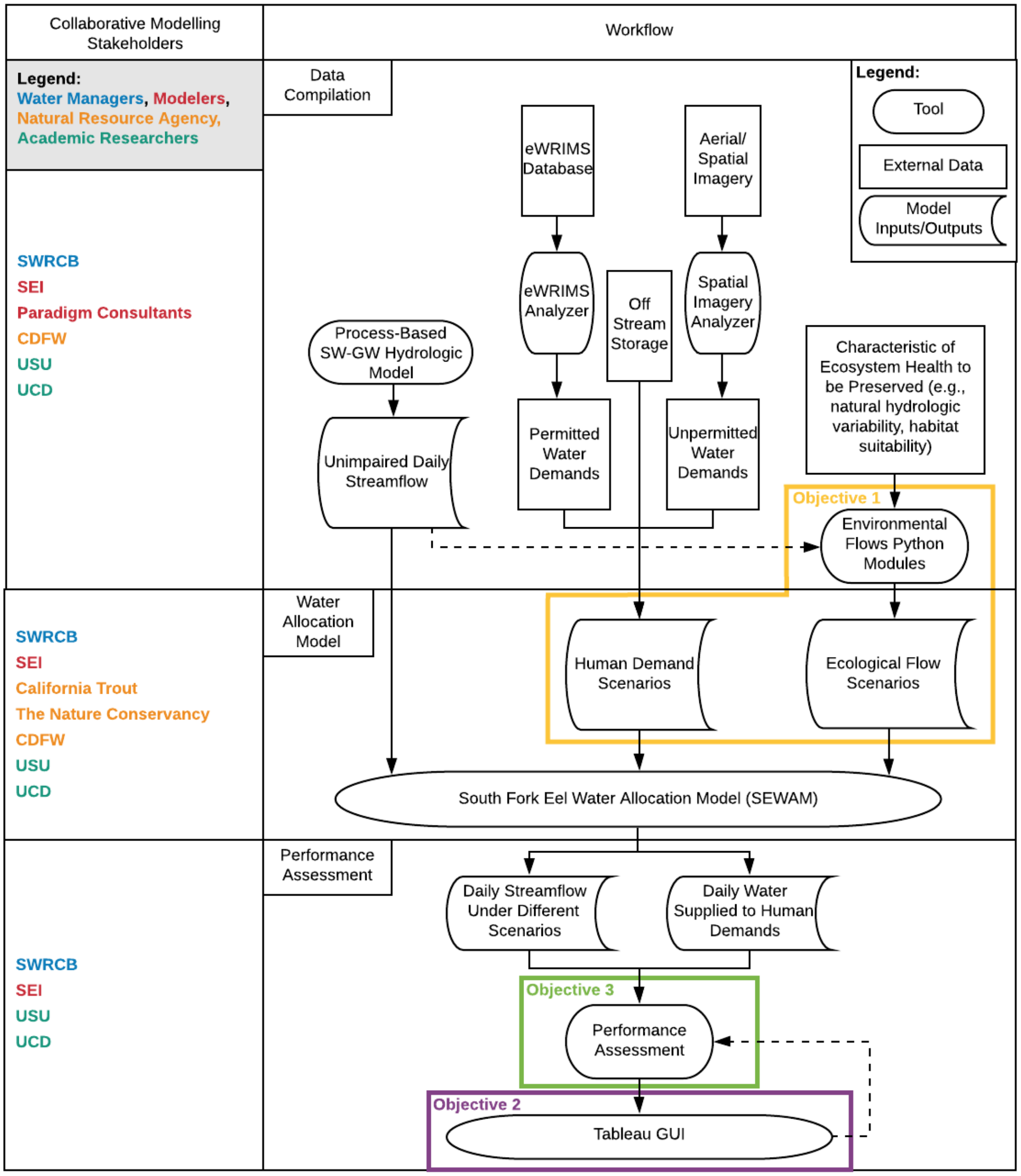


Figure 2 - Overall DSS workflow with stakeholders and thesis research objectives identified.

South Fork Eel Water Allocation Model (SEWAM)

The watershed water allocation model was developed by Stockholm Environmental Institute (SEI) using the Water Evaluation and Planning System (WEAP) software and is referred to as the South Fork Eel Water Planning Model (SEWAM). SEWAM uses unimpaired daily stream-flow calculated in a separate, process-based hydrologic model developed by Paradigm Consultants for water years 1995-2017. This hydrology model also simulates groundwater pumping by estimating surface to ground water interactions. At a high level, SEWAM takes the unimpaired flow, estimates groundwater pumping, removes human demands in the form of diversions, and evaluates what remains to determine if it is able to satisfy the ecological water needs of each location. The ecological water needs are represented by a series of ecological scenarios, each with its own IFT for each location, discussed in more detail below. Permitted water demands were estimated using a tool developed by researchers at SEI called the eWRIMS Analyzer, which accumulates permitted and reported amounts of each water right in the location of interest from eWRIMS. These are based on the values for all appropriative and most riparian water rights. Unpermitted diversions were estimated using aerial imagery.

Permitted and unpermitted demands divert water differently. SEWAM accounts for this by first diverting unpermitted demands, which will remove as much water as needed regardless of other policies in place, then by evaluating how much of the permitted demands can be supplied based on the IFT. If the IFT is much higher than the stream-flow after unpermitted demands are diverted, less permitted demands, if any, will be allowed to be diverted. This is representative of how permitted water diverters actually operate, since they are only allowed to divert when the IFT is met on each day. SEWAM has many considerations for adjustments that can be made to the permitted and unpermitted human demands as well as ecological demands, which are explored further below.

Collaborative Modeling

A collaborative modelling approach was used to develop the DSS, as well as to complete the research objectives performed in my research. SEWAM is modular in that any time series of IFTs and estimates of human demands can be used and evaluated at any location of interest and can therefore be run iteratively as understanding of the system improves. There are also many ways the results can be broken down and visualized in the user-interface, as will be discussed below. Due to these complexities, and the many interested parties. Collaborative modeling was used to develop the entire toolset which includes SEWAM, a dynamic web-based user-interface to aid in analysis, and the supplemental research questions and analyses. Stakeholders involved in the collaborative modeling process of this project involved decision-makers (SWRCB), consultants (SEI, Paradigm), basin stakeholders (CDFW, the Nature Conservancy, and California Trout), and academic institutions (Utah State University, University of California Davis).

To ensure the visions of all of these stakeholders were considered, shared vision planning methods were used which include three pillars: structured stakeholder engagement, collaborative modelling, and water resources planning methods (Cardwell and Langsdale, 2011). Structured stakeholder engagement was accomplished by continuous and periodic interactions with stakeholders, definition of ground rules for how stakeholders interact and send or receive input, roles and responsibilities for each stakeholder, and well-defined communication channels and feedback processes. Collaborative modeling and water resource planning were performed in these structured stakeholder engagements by iteratively working through and adjusting model components based on stakeholder input.

In the following sections, I describe my three research objectives, how they were achieved, and how they advance the larger goals of the project. Due to the collaborative nature of this project, the research presented here describes what was done in the project as a whole, with the specific roles I played and tasks performed as part of this large project highlighted. First, the human and ecological scenarios are described with emphasis on why they were selected and how they were calculated, if applicable. Then, I discuss the development of the dynamic user-interface and visualizations geared towards communicating SEWAM model results effectively. Finally, the additional analyses I performed outside those already offered by the user-interface are described, with emphasis on SEWAM model results analysis. All of the analyses I completed for this research, outside of the specific SEWAM and Tableau modeling tools, were performed using python and the scripts will be made publicly available (See Data Availability section).

Objective 1 – Define Human and Ecological Scenarios

A set of human demand scenarios, or human scenarios, and ecological flow scenarios, or ecological scenarios, was defined to evaluate in the DSS through collaboration with stakeholders. The human scenarios were included to adjust human demand parameters, such as amount of demands and off-stream storage availability, to cover current and future uncertainty in estimations of these parameters. These scenarios were mostly included and selected based on guidance from SWRCB and are included in my thesis to provide crucial understanding of the capabilities of SEWAM. The ecological scenarios are different methods of setting IFTs at each location based on top-down and bottom-up approaches.

My specific contributions were to guide analyses of the proposed human scenarios and provide feedback on them, and to calculate the IFTs associated with each ecological scenario. Therefore, my contributions were more prevalent to the ecological scenarios, since I worked to not only the develop the list of scenarios, but also wrote python scripts that are able to be used on any input hydrology and habitat suitability data to generate time series of IFTs for each ecological scenario. All combinations of the human and ecological scenarios were then run in SEWAM to evaluate the impacts on the amount of water delivered to humans and left instream for the ecosystem.

Human Scenarios

The human scenarios were developed with the intent to represent a wide range of possible human demands and account for uncertainty in the both permitted and unpermitted demand determinations. We defined a ‘baseline’ human scenario which is meant to estimate historic water demands based on historic water management policies and estimations of permitted and unpermitted demands. Adjustments were made in human scenarios outside this to change a parameter related to permitted or unpermitted demands. These alternative human scenarios are of particular interest due to their ability to provide water supply performance for water management parameters and determine which are of most importance. They also provide the ability to understand how water supply performance may change in the future given large changes to current operating conditions.

Off-stream storage was adjusted to determine how varying amounts of storage affect the availability of water for either permitted or unpermitted demands. While permitted diverters that are monitored using eWRIMS often have access to off-stream storage, unpermitted diverters have varying levels of access to off-stream storage which are difficult to quantify with aerial imagery due to densely forested canopies and intentional efforts to conceal unpermitted grow sites (Dillis et al. 2019). In light of this high uncertainty, varying amounts of off-stream storage availability for unpermitted demands were considered, with the default amount being no storage. Additionally, it is of particular interest to determine the impact of bringing these diverters into compliance so their diversion practices will be more responsive to the ecosystem needs and the policies enacted by water managers.

Ecological Scenarios

A mixture of top-down and bottom-up approaches were used to develop IFTs that correspond to each ecological scenario. Several top-down approaches were considered, including Tessmann (Tessmann 1980), Percent of Flow (POF, Flannery et al., 2002), Modified Percent of Flow (MPOF, Miearu et al., 2017), North Coast Instream Flow Policy (NCIFP, SWRCB 2014), and Functional Flow Metrics (FFM, Yarnell et al., 2019; Patterson et al., 2020) methods. One bottom-up method was also used that considered site-specific discharge - hydraulic habitat relationships (Bovee 1982) at subset of locations, which are here referred to as Ecological Performance Percentile (EPP) scenarios (Table 4).

There are two major outcomes of the methods described in this section. The first was a python module that allowed for the calculation of daily IFTs pertaining to each of the ecological scenarios. This module uses the unimpaired hydrology, habitat suitability, functional flow metrics, and calculated Tessmann requirements as inputs for each location. The second major outcome was the IFTs themselves, which had to be processed and formatted for use as inputs to SEWAM.

Tessmann Method

The Tessmann method is a top-down approach for determining IFTs based on the ratio of mean monthly flow to mean annual flow. When mean monthly flow was less than 40% of mean annual flow, the monthly IFT was set as the mean monthly flow. When 40% of the mean annual flow was between 40% of the mean monthly flow and the mean annual flow, the monthly IFT was set as 40% of the mean annual flow. Otherwise, when 40% of the mean monthly flow was greater than 40% of the mean annual flow, the IFT was set as 40% of the mean monthly flow (Tessmann 1980, Książek et. al, 2019). The Tessmann method of determining instream flow targets was deemed appropriate by the SWRCB and CDFW (SWRCB, 2017) and is used in California for determining permitted cannabis surface water diversion rates via the 2019 interim state policy.

Percent of Flow (POF) Method

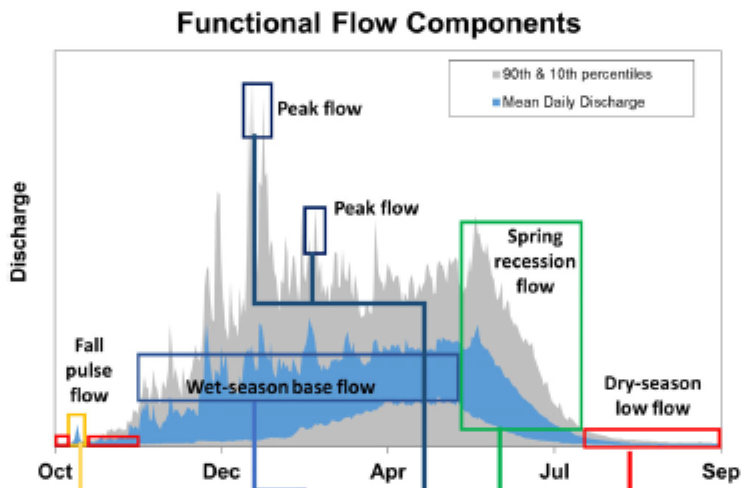
The POF method calculates IFTs as a set percent of the unimpaired flow at a location of interest. For example, if 100 cfs occurs naturally at some location and time and the POF scenario is 70%, the IFT is 70 cfs at that time. POF-based methodologies have been used in systems in Southwest Florida, the United States’ Great Lakes region, and Maine (Flannery et. al, 2002, Richter et al., 2012). The final list of POFs considered is POF 75%, 80%, 90%, and 95%.

Modified Percent of Flow (MPOF) Method

MPOF is a modified version of the POF technique (Miearu et. al 2017). Rather than taking a set percentage of the flow as in POF, the 90th percentile average monthly flow was calculated (i.e., the flow that is exceeded by 90% of monthly flows over the period of record [POR]) for a particular location. Then, 10% of the 90th percentile monthly flow was set as the maximum allowable diversion at that location for that month. The IFT is therefore the unimpaired flow minus this calculated maximum allowable diversion on each day. This technique stands out from the others due to the consistency of the allowable diversions from year to year, regardless of climate, rather than the consistency of an IFT from year to year. This allows the IFTs to retain much of the annual and interannual hydrologic variability of unimpaired stream-flow.

Functional Flow Metrics (FFM) Method

The functional flows approach to setting IFTs was based on the hypothesis that key aspects of the unimpaired annual flow regime, or functional flow components, support critical physical and biogeochemical processes that maintain native river ecosystems (Yarnell et al 2015; 2019). FFMs refer to features of the annual hydrograph that quantify functional flow components. For example, FFMs include the start date of certain seasons (e.g., dry or wet season), dry season baseflow magnitude, and peak flow magnitudes and frequencies. An example hydrograph from Yarnell et al. 2019 illustrates the five functional flow components identified as important for California rivers, and the associated FFMs (Figure 3).



	Functional Flow Components				
Flow Characteristics	Fall Pulse	Wet Baseflow	Peak Flow	Spring Recession	Dry Low Flow
Magnitude	X	X	X	X	X
Timing	X	X	X	X	X
Duration		X	X	X	X
Frequency			X		
Rate of Change				X	X

Figure 3 - Example hydrograph with identified Functional Flow Metrics (from Yarnell et al. 2019)

The unimpaired ranges (10th to 90th percentile) of 24 FFMs were predicted for every NHDplusV2 stream reach in California under three water year types (dry, moderate, and wet) (Grantham et al *in prep*). Given the limited control water managers have on instream flows in the study area and the distributed nature of them, it is unfeasible to require IFTs related to many of the functional flow components, such as the fall pulse event. In the study area and similar systems, unlike reservoir-regulated systems where water storage is more closely balanced with annual water supply, such events are entirely dependent on both spatially and temporally-varying local climate conditions with water management decisions having little effect. Therefore, the FFM-based IFTs were only based on median values for dry and wet season start timing and baseflow magnitude for each water year type, which were classified as either dry (>67% exceedance), moderate (33-67% exceedance), or wet (<33% exceedance).

North Coast Instream Flow Policy (NCIFP) Method

The NCIFP method is the current method for determining diversion allocations within five counties of Northern California (Marin, Sonoma, Mendocino, Humboldt, and portions of Napa) and includes coastal stream from the Mattole River in Humboldt County to San Francisco and coastal streams entering northern San Pablo Bay (SWRCB, 2014). This policy was developed with a particular focus on protecting anadromous salmonids such as steelhead trout, coho and chinook salmon. The diversion, or *non-forbearance* period, during which diversions are allowed only when stream-flow is above the minimum bypass flow ($Q_{MBF,}$ Table 1), runs from December 15 to March 31 such that diversions only occur during the winter high-flow season. Outside this range of dates, no diversions are allowed. On days within the diversion season that exceed Q_{MBF}, the maximum cumulative diversion rate (Q_{MCD}) at a location is equivalent to 5% of bankfull flow. For a detailed example, see Appendix B.

Table 1 – Calculation of minimum bypass flow using mean annual unimpaired flow and watershed drainage area for the North Coast Instream Flow Policy.

Contributing Area	Minimum Bypass Flow Formula
1 square mile or smaller	$Q_{MBF} = 9.0\ Q_m$
Between 1 and 321 square miles	$Q_{MBF} = 8.8\ Q_m(CA)^{-0.47}$
321 square miles or larger	$Q_{MBF} = 0.6\ Q_m$

Ecological Performance Percentiles (EPP) Method

The EPP approach (Bovee 1982) uses area weighted suitability, which is a unitless metric that evaluates the suitability of hydraulic habitat at a given location, to determine IFTs. It was calculated by dividing each individual reach at a given discharge into cells where each cell contains a depth and velocity and determining how much of the area is suitable at the given flow. In my thesis, suitable habitat conditions were determined for the juvenile life stage of steelhead salmon by CDFW at a range of discharges. The relationship between area weighted suitability and discharge is called an Ecological Performance Function. These functions were provided for five out of the available 11 locations.

Determination of IFTs was performed using water month type (WMT) designations using the unimpaired hydrology data. Water month type was calculated from mean monthly flow based on modeled unimpaired daily stream-flow over water years 1995-2019. Critically dry (CD) months are exceeded by >90% of the mean monthly flows, dry months are exceeded by 70-90%, below median months are exceeded by 50-70%, above median are exceeded by 30-50%, wet months are exceeded by 10-30%, and extremely wet (EW) months are exceeded by <10%. Once the flow data was separated into the WMTs, the daily flows in each WMT were used to determine corresponding area weighted suitability values for that location. Then, percentiles of these values were taken for each combination of WMT and calendar month. These were then converted back to flow so that different percentiles could be translated into IFTs. Since there is an intermediate flow value that has a peak suitability in the ecological performance function, IFTs were not provided if they were determined to be higher than the flow that corresponds with the maximum suitability at each location. There were 6 percentiles taken resulting in 6 ecological scenarios – 10^{th}, 25^{th}, 50^{th} (or median), 75^{th}, 90^{th}, and 100^{th} (or max).

Performance Assessment

Water resources performance assessments are often based on frequency or magnitude of success or failure of meeting water demands (Hashimoto et al., 1982; Fowler et al., 2003; Haro-Monteagudo et al., 2020; Purkey et al., 2018; Sandoval-Solis et al., 2011). In this research, the techniques Lane et al. (2020) proposed were adopted including frequency reliability, volumetric coverage, and deficit. We also considered impairment to evaluate the amount of water removed from the stream relative to unimpaired. In order to obtain one value of performance for a location and scenario combination, performance was broken into three components: performance metric, demand type, and temporal aggregation. Demand type indicates the type of demand to be considered, including ecological demands, permitted and/or unpermitted human demands in the local sub watershed, or permitted and/or unpermitted human demands in the total contributing area. Finally, temporal aggregation was performed to collapse performance time series into a single value over a period of interest. This can be a calendar month, WMT, dry/wet season, or the entire POR. Each of these temporal filters were applied to calculate performance with respect to each of three types of water demands – ecological demands, local sub watershed human demands, and total upstream human demands, resulting in 451 ways to quantify performance which are discussed in detail below.

Human and ecological performance were evaluated using several performance metrics including volumetric coverage, frequency reliability, deficit (Lane et. al 2020), and impairment. The first three of these metrics were selected because they encompass the magnitude (volumetric coverage and deficit) and frequency of demands being met. Impairment was added to begin to understand the actual impact the human and ecological scenarios had on the ecosystem by determining how much water was removed from the stream compared to the unimpaired flow. Impairment also differs from the other three because it is independent of the demand magnitude, while the other three are directly impacted by it – scenarios with higher demands will have worse frequency reliability, volumetric coverage, and/or deficit than scenarios with lower demands.

Volumetric coverage was calculated as the ratio of the total flow rate of water supplied to demands to the total flow rate of water demand over a given period of time, as shown in Equation (1). Volumetric coverage is always less than or equal to 100% over any time, since, in human demands, the flow rate supplied will never exceed the demand, and in ecosystem demands, excess water is not counted.

$$Rel_{Volume}^{i} = \frac{\sum_{t=1}^{n} \left(X_{Supply,t}^{i} \right)}{\sum_{t=1}^{n} \left(X_{Demand,t}^{i} \right)} \tag{1}$$

Frequency reliability was calculated as the number of time steps a requirement was fully met (or where the deficit was zero) divided by the total number of time steps, as shown in Equation (2) where n_{D0} is the number of time steps that had a deficit value of zero, and n is the total number of time steps.

$$Rel_{time}^{i} = \frac{n_{D0}}{n} \tag{2}$$

Daily frequency reliability indicates the percentage of days that water requirements are met. In this research, the frequency that 50%, 75%, and 90% of demands were met was also calculated for both human and ecological demands.

Deficit was calculated as the difference between the flow rate of water demanded and the flow rate of water supplied. Any flow above the requirement does not count toward the deficit (i.e., there is no negative deficit if more than enough flow is provided). The calculation for deficit is shown in Equation (3) where $X_{Demand,t}^{i}$ is the total amount of water demanded by humans over time t at location i and $X_{Supply,t}^{i}$ is the amount supplied for these demands over time t at location i.

$$Def_{t}^{i} = X_{Demand,t}^{i} - X_{Supply,t}^{i} \tag{3}$$

Finally, impairment was calculated as the difference in stream-flow between the scenario combination of interest and the scenarios that have no human or ecological demands. Ideally, this difference would be between the true unimpaired stream-flow and the stream-flow in the scenario. However, since SEWAM is configured to include groundwater pumping in every scenario, there is water lost to both groundwater pumping and surface diversions when surface water demands are implemented. This is important because if the scenario stream-flow, which has groundwater pumping, is subtracted from the true unimpaired stream-flow, which has no groundwater pumping, the impact of the surface diversions would be indiscernible from the impact of groundwater pumping. Therefore, the stream-flow in the scenario with no demands was used to represent the unimpaired flow when calculating impairment so the impacts of the surface diversions under different human demand scenarios could be isolated and analyzed.

We also introduced standardized impairment which weights impairment by the mean flow in the time period of interest. This is important because the same amount of impairment at one location and time of year as another can provide drastically different impacts to water availability due to change hydrology. For example, a 1 cfs impairment when the mean flow is 100 cfs is much less important than a 1 cfs impairment when the mean flow is 10 cfs. Therefore, standardized impairment (SI) was calculated by dividing the impairment by unimpaired flow. SI is discussed and analyzed in this research as a percent (e.g., 10% SI indicates that 10% of the unimpaired flow was removed from the stream by implementing the ecological and human scenario). SI is calculated as a mean across the temporal aggregation of interest.

Each of these performance metrics was calculated as an absolute value and a relative value, defined here as the difference between the selected performance metric in the given scenario combination and the baseline scenario. The baseline human scenario is described below and the baseline ecological scenario is the No Demands scenario.

Objective 2 –Develop Assessment and Visualization Tool

SEWAM results were input to a dynamic web-based user-interface designed in Tableau™ (Tableau 2021) to provide visualizations of performance to stakeholders (Figure 2). Tableau was selected due to its powerful user interface capabilities, both in data processing and visualization. This tool was developed to help answer specific questions about the general state of the system under the different human and ecological scenarios. This includes showing temporal and spatial trends in performance, as well as comparing performance between different scenarios. The temporal analyses are included to evaluate the large annual and interannual hydrologic variability and how it impacts water availability for the different demands. Spatial analyses are also important since the human demands are spatially distributed in this watershed with locations of varying hydrologic characteristics having varying amounts of human demand. Finally, due to the numerous ecological and human scenario combinations, providing the ability to compare both absolute and relative values of performance among scenarios as well as other characteristics of each scenario like magnitude of demands is essential.

Development of the GUI was led by SEI, and my contributions included participating in structured stakeholder interactions to provide feedback on the effectiveness and accuracy of the visualizations, descriptions and overviews of the scenarios, SEWAM, and the GUI overall, as well as suggestions of additional visualizations to include (Figure 2). The development of this GUI was overseen by the SWRCB with researchers at USU (including myself) and UCD guiding its progress. The outcome of this objective is the publicly-available GUI containing model results that is designed to be used by stakeholders, but is also available to any others who may find the information useful like academics.

Objective 3 – Supplemental Scenario Analysis

The user-interface was designed to answer general questions that stakeholders may have about the study watershed, while my specific research questions required some additional analyses that complement those within the larger DSS collaborative project (Figure 2). The outcome of this objective is to address the specific research questions laid out above to provide a deeper understanding of the trends in performance including trends in performance by location, climate, water management decisions, as well as interactions between these factors.

Reach Setting Parameters

Trends in performance were analyzed against reach setting parameter to determine if any of these characteristics of a location had an impact on performance. A *reach setting parameter* (RSP) is defined here as a static attribute of the specific stream reach or upstream drainage area. A description of the RSPs used in this analysis are laid out in Table 2.

Table 2 - List of Reach Setting Parameters (RSPs). Num is an abbreviation for numeric variables, while Cat is an abbreviation for categorical variables. GC was obtained from Byrne et al (2020) and GS was obtained from Hahm et al 2019 and Langenheim et al. 2013. The other RSPs are explained in the text.

Full Name	**Code**	**Type**	**Units**	**Min to Max (Num) or All Values (Cat)**
Contributing Area	CA	Num	mi^2	2.7 to 26.1
Geomorphic Classification	GC	Cat	-	SFE04, SFE05
Geologic Setting	GS	Cat	-	Franciscan Yager Terrane (Yg), Tertiary cover (QTw), Franciscan Central Belt (C)
Upstream Demands – Total Value of Permitted and Unpermitted Demands	UDV	Num	cfs	0.00025 to 0.13
Upstream Demands – Unpermitted or Permitted Dominant	UDD	Cat	-	Unpermitted and Permitted
Upstream Demands – Permitted Type Dominant	UDP	Cat	-	Domestic, Irrigation, Permitted Cannabis
Upstream Demands – Total Per Unit Area	UDA	Num	cfs/mi^2	0.000091 to 0.0086
Upstream Demands – Proportion of Mean Annual Flow	UDM	Num	Unitless	0.000028 to 0.0038
Upstream Demands – Proportion of Lowest Monthly Flow	UDL	Num	Unitless	0.00085 to 1.01
Upstream Demands – Proportion Unpermitted Demands per Unit Area	UDUA	Num	cfs/mi^2	0.000091 to 0.0025
Upstream Demands – Proportion Unpermitted Demands to Mean Annual Flow	UDUM	Num	Unitless	0.000028 to 0.0016
Upstream Demands – Proportion Unpermitted to Lowest Monthly Flow	UDUL	Num	Unitless	0.00085 to 0.37
Upstream Demands – Proportion Unpermitted to Permitted in Summer	UDPS	Num	Unitless	1.74 to 3.73

Each of the RSPs was selected for its potential influence on human and/or ecological water supply performance based on the following hypotheses. UDA and Contributing area were used to determine if there was a tradeoff between larger areas having more water available while also containing more demands. A geomorphic classification presented in Guillon et al. (2019) was considered to distinguish high-slope headwater locations from low-slope main stem locations. This scheme classifies stream forms occurring at the 10-20 channel width scale based on channel attributes such as slope, bank-full width, topographic variability attributes like coefficients of variation of width and depth, sediment size, and valley confinement. Geologic setting is hypothesized to have more of a hydrologic impact on performance – infiltration rates, storage capacity in soil, runoff rates, and lateral groundwater rates (Lane et al. 2017; Hahm et al 2019). These all impact the rate that water moves from precipitation to instream discharge. If a location is in a geologic setting with slower transition of water from precipitation to discharge, this could be helpful in the dry season if the system is able to store water for a longer time.

The remaining RSPs are related to upstream demand. These RSPs were considered in order to evaluate tradeoffs between amount of demands and available water in the form of instream flow. UDV was calculated as the total amount of permitted and unpermitted demands at a location. However, it does not take into account any hydrologic characteristics of a location. For example, a location with mean annual flow of 100 cfs is going to be a lot less impacted by 2 cfs of demands than a location with mean annual flow of 10 cfs. Therefore, UDA was considered to determine if a high density of demands per unit area had an impact on performance. Similarly, UDM and UDL were considered to explore how much of different representative flows (mean annual flow and lowest monthly flow, respectively) at a location are needed to be removed from the stream to human demands weighted by characteristics of the hydrology at that location. UDL indicates how high demands are during the time of year when there is the least amount of water naturally available, which is particularly critical in this watershed. UDP was added to see if locations where certain types of permitted demand dominate in the contributing area had significantly different performance. This could be tied to total amount of volumetric demands in that locations where agriculture dominates could have more demands in general.

The rest of the demand RSPs (UDD, UDUA, UDUM, UDUL, and UDPS) seek to evaluate the impact of unpermitted demands. Unpermitted demands were given special attention since unpermitted users divert water with no regard for other users or the instream flow targets in place. Therefore, if there are more unpermitted demands relative to instream flow or permitted demands, they will have a larger impact. UDD was considered to see if performance was significantly different in locations where unpermitted or permitted demands were more prevalent. UDUL is analogous to UDL except that it only considers unpermitted demands to demonstrate if having a greater proportion of the lowest mean monthly flow demanded by unpermitted diverters has a more direct impact on water allocation than the same metric for all demands. The same applies to UDUA as compared to UDA and UDUM as compared to UDM. They are the same metrics except that they only consider unpermitted demands weighted by contributing area and mean annual flow, respectively. UDPS was included to assess the impact of unpermitted demands relative to permitted demands on the low-flow times of year. Specifically, the low-flow times of year are the months of July to September. This ratio is hypothesized to be more important in the low-flow summer when there is much less water that can be spared to unpermitted demands.

RSP values were assembled from a variety of methods including GIS analysis and various classification schemes of other works. Contributing area, geomorphic classification, and geologic setting were assembled by GIS analysis, with the datasets being provided by Guillon et al. (2019) and Hahm et al. (2019) for geomorphic classification and geologic setting, respectively. Demand-based RSPs were calculated using model inputs and unimpaired hydrology for each location. Specifically, UDV, UDA, UDL, and UDM were calculated using mean of monthly unpermitted and permitted demand flow rates, while UDUA, UDUL, and UDUM were calculated using mean of monthly unpermitted flow rates. UDPS was calculated by taking the ratio of mean of monthly unpermitted demands to mean of monthly permitted demands from July to September.

UDD was found by determining whether the sum of monthly demands was greater for permitted or unpermitted demands. All permitted and unpermitted demands were constant across each year for each calendar month.

Screening Process

Given the numerous permutations of model characteristics including scenarios, performance metrics, and locations outlined above, a quantitative screening process was performed to constrain this analysis to the most significant results. Specifically, key model characteristics were selected to highlight specific and/or significant management implications that could have significant impacts on water system performance. For example, the Cannabis Junior Priority scenario has specific management implications since it allows for the assessment of performance when unpermitted cannabis diverters are brought into compliance, while the Cannabis Demands 10x scenario has significant impacts on performance due to much more water being removed from the stream than estimated. The scenarios with the largest effect on performance were determined by analyzing relative performance by scenario, location, and climate condition.

Tessmann, MPOF, and EPP scenarios were selected for focused analysis based on their management implications and the relative amount of water required. Tessmann was selected because this method is currently being used to determine surface water diversion rates for cannabis uses throughout every region of California (SWRCB 2019). MPOF was selected because it has been developed as a simple top-down approach specifically to set diversion limits in this type of system and is of interest to watershed stakeholders. NCIFP is also currently used in multiple regions of California, but is similar to MPOF in that they both determine diversion limits rather than IFTs directly. In contrast to these top-down approaches, EPP scenarios provide specific information about habitat quality for juvenile steelhead salmon.

The key human scenarios selected were Baseline, Cannabis Demands 10x, Cannabis Junior Priority, and eWRIMS Storage Off. The baseline human scenario is of interest because it provides a starting place in the analysis. Cannabis Demands 10x was chosen because it highlights the real impact of the unpermitted demands in the system. As will be discussed in the coming sections, Cannabis Demands 10x has the largest impact on performance relative to baseline, especially in the summer months. Conversely, Cannabis Junior Priority has a large impact on improving performance relative to baseline, especially in the summer as well. Cannabis Junior Priority has a lot of similarities to Cannabis Demands 0x, so was useful in evaluating if Cannabis Demands were removed as well as brought into compliance. Finally, eWRIMS Storage Off was considered because it explores the impact off-stream storage has on the ability to meet demands and has a large impact on performance.

LOIs 2090 and 2240 were selected for a more in-depth study of individual locations to capture distinct watershed settings and contributing areas (Figure 4). LOI 2090 is the outlet of Redwood Creek, and thus has the largest contributing area. Conversely, LOI 2240 has a low contributing area for this set of locations. Comparing results for these two locations will highlight tradeoff between natural water supply and demands. We hypothesize that there could be a threshold contributing area beyond which the cumulative water demands exceed natural water availability in these hydrologic conditions.

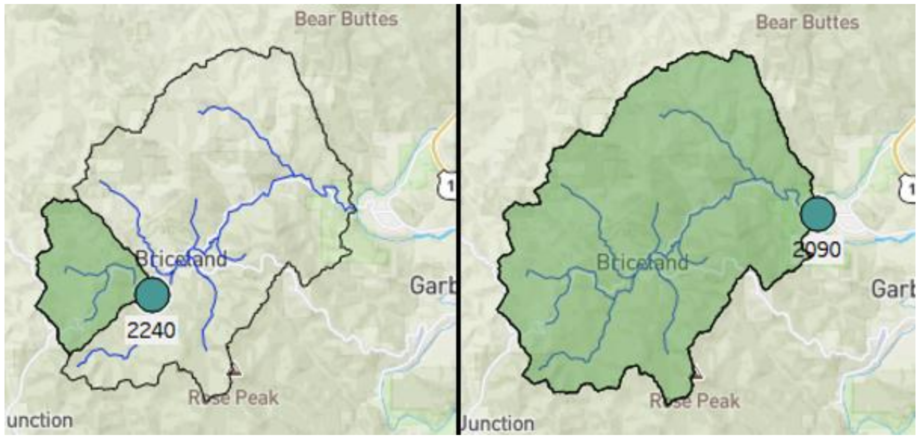


Figure 4 - Map showing location and contributing area of LOI 2240 and LOI 2090. These locations were focused on in the analyses.

The three key performance metrics considered in subsequent analyses were frequency reliability with respect to (1) instream flow and (2) permitted human water demands and (3) mean standardized impairment for the POR, January, and July. Frequency reliability for instream flows and permitted demands are correlated; since permitted human demands occur at a lower priority than providing water to ecological demands, less water will be supplied to permitted human demands when IFTs are set to higher values and performance will drop. Standardized impairment can be compared between locations since it is a proportion of total unimpaired flow, and is a more direct way of analyzing ecosystem health since it is a measure of how much water was removed from the stream. Evaluating performance in January and July is intended to capture the varying trends in the high-flow and low-flow seasons, respectively. Interannual hydrologic variability was considered by analyzing performance based on these metrics in critically dry and critically wet WMTs.

Question 1 – Reach Setting Parameters

To determine how human and ecological performance vary at different locations based on RSPs **[Q1]**, general performance trends were evaluated with respect to the different RSPs at key locations by plotting and qualitatively evaluating key performance metrics against each RSP. Each of these relationships were then visually evaluated across key scenarios to determine which RSPs and performance metrics are most strongly correlated. More robust statistical comparisons were considered but not used due to the small sample size at this stage of the overall project. This analysis was performed under the baseline human scenario across the MPOF and Tessmann ecological scenarios to isolate the effects of the RSPs.

Question 2 – Human Scenarios

The second research question **[Q2]** explored the relative impacts of different human scenarios on performance under different climate conditions, as well as how these impacts vary by RSP. To answer this question, human and ecological performance values were extracted at every location under every human scenario for a single instream flow scenario. For each ecological scenario and across scenarios, relative performance of human scenarios with respect to the baseline human scenario was then calculated to determine which human scenarios had the largest impact on performance relative to current conditions. Distribution of relative performance across locations were plotted using violin plots and box and whisker plots. Similarly to the results of question 1, performance distributions were qualitatively analyzed for trends.

For the second part of this question, these performance trends were also evaluated with respect to RSPs. The relative change in performance from baseline was plotted against each of the RSPs, and a linear model was fit to the data. These plots were also qualitatively analyzed to determine if different ranges of RSP values led to different values of relative performance. Multiple models were considered to look at relationships between relative performance and RSP including first and second order polynomial models. However, due to the small sample size of locations, it was deemed unnecessary to do an in-depth statistical analysis to determine the proper model to be used, since trends in performance that are actually representative of the system are virtually impossible to distinguish from statistical noise.

For numeric RSPs, relative performance was plotted against RSP with a linear model to determine if different values of these RSPs generally correspond to different human scenarios becoming more important. In the context of this research question, ‘importance’ is a term used to discuss the magnitude of the relative performance value, whether positive or negative. For categorical RSPs, the distribution of the relative performance was plotted to determine if different categories of RSP lead to differing relative performance distributions.

Question 3 – Climate

The third research question **[Q3]** considered the impact of natural hydrologic variability on human and ecological performance. Model performance was evaluated with respect to month and water month type to consider the impacts of both annual and interannual hydrologic variability. Plots were generated to show performance in each time interval for a single ecological scenario across all human scenarios at a given location, as well as performance for a single human scenario across all ecological scenarios at a given location. Surfaces were also created that show, for a given ecological and human scenario at a given location, how performance varied by month and water month type. These plots highlight which month and water month type combinations have the greatest impact on performance.

Question 4 – Climate & Management Relative Sensitivity

The final research question **[Q4]** considered relative impacts of human management decisions on performance compared to the impact of natural hydrologic variability. The plots created for question 2 (that show the relationship between performance and month or WMT over all human scenarios for a given ecological scenario or vice versa) were used to answer this question by calculating: (1) management scenario variability and (2) climate variability. Management scenario variability refers to the maximum performance difference between scenarios within a single month or WMT. Climate variability refers to the difference in performance between the best and worst performing month or WMT for the ‘baseline’ scenario. Specifically, when comparing across human scenarios, the baseline human scenario was used to determine climate variability. When comparing across ecological scenarios, whichever ecological scenario introduced the greatest climate variability was used since there is no ecological scenario that represents ‘normal’ conditions. The plots were annotated in this way so the values can be easily compared by looking at each plot.

The ratio of the management scenario variability to climate variability was calculated for each ecological or human scenario and location and used to generate heat plots. We define this ratio as the Climate & Management Relative Sensitivity (CMRS) metric. A CMRS value greater than one indicates situations where the variability introduced by the different scenarios is greater than the natural climate variability, whereas a CMRS value less than one indicates climate variability has a greater role on performance than scenario variability. CMRS was calculated and compiled for each ecological scenario across all of the human scenarios, as well as for each human scenario across all of the ecological scenarios. CMRS was analyzed by month and WMT to determine how the scenario impacted performance relative to the annual and interannual variability, respectively. In the heat plots, locations were sorted from smallest to largest contributing area to explore trends with respect to this metric.

RESULTS

Objective 1 – Defining Water Management and Instream Flow Scenarios

In total, 11 human scenarios (Table 3) and 15 ecological scenarios (Table 4) were considered in the DSS for the Redwood Creek watershed. 150 unique scenario combinations were simulated in SEWAM at each location of interest – the outlet of Redwood Creek (LOI 2090) and the headwater location (LOI 2240).

Human Scenarios

The human scenarios considered in this study span a large range of permitted and unpermitted demand amounts, off-stream storage capacities, and demand priorities (Table 3). The baseline scenario was defined to have no storage available for unpermitted cannabis demands, the amount of permitted demands defined by the total amount specified for each water right in eWRIMS, and with eWRIMS off-stream storage available. All but one of the other scenarios intend to isolate the impact of changing a single water demand or storage parameter relative to baseline. The final scenario (No Demands) considers system behavior when all cannabis and eWRIMS demands are removed to assess system performance in the absence of human influences.

Table 3 – Full list and description of current human scenarios.

Human Demand Scenarios	**Description**
Baseline	Current conditions are simulated, assuming (a) no unpermitted cannabis storage, (b) unpermitted cannabis and unreported domestic demands have highest priority to reflect a lack of enforcement, (c) permitted demands are based on permitted values, and (d) permitted demands may utilize storage.
Unpermitted Cannabis Demands (0x, 2x, 10x)	Unpermitted cannabis demands are set to 0x, 2x, or 10x of baseline estimates. This accounts for the high degree of uncertainty in present cannabis demands as well as future trends.
Unpermitted Cannabis Storage (1 Month, 3 Months, Legal)	Unpermitted cannabis demands decrease summer diversions and increase diversions from Nov-Mar to store a maximum volume equal to the highest 1 or 3 months of demands. In the legal storage simulation, unpermitted cannabis demands may only divert from Nov-Mar and must store water for use in all other months, consistent with the water right requirements for cannabis cultivation in California. These scenarios reflect uncertainty surrounding storage patterns for unpermitted cannabis diversions and the possible effects of bringing unpermitted cannabis diverters into compliance.

Unpermitted Junior Priority	Unpermitted cannabis and unreported domestic demands have lower allocation priority than environmental and permitted demands to simulate possible effects of bringing unpermitted cannabis diverters into compliance.
Permitted Water Demands, Reported Water Use	Permitted demands use *reported* rather than *permitted* water use data from eWRIMS. This simulation encompasses uncertainty surrounding water demands and more closely approximates the amounts that users have reported in the past, rather than the maximum legal limit.
Permitted Water Demands, Storage Off	Permitted demands do not use storage, and as a result have higher diversions in summer and lower diversions in winter. This simulation reflects uncertainty surrounding water right storage patterns, and demonstrates the impacts of water right storage.
No Demands	Permitted water rights, unpermitted cannabis, and unreported domestic demands are turned off. This simulation captures the system response without surface water demands.

Seven scenarios involve adjustments to unpermitted demands (Table 3). Unpermitted Cannabis Demand scenarios adjust the amount of unpermitted diversions including options for completely removing them, doubling them, or multiplying them by 10. These will be referred to as the Cannabis Demands 0x, Cannabis Demands 2x, and Cannabis Demands 10x scenarios. These are meant to show the relative impact of unpermitted cannabis demands on the system and help water managers understand how future cannabis demands may impact the system if they are to significantly change in amount. Then, the Unpermitted Cannabis Storage scenarios add different amounts of off-stream storage for unpermitted cannabis diverters. The first two provide enough off-stream storage for the highest month or 3 months of water required at a given location. The third allows diversion only during the legal permitted cannabis water right diversion period from November to March, with use from storage available for the rest of the year. The amount of off-stream storage provided in this scenario is equivalent of the amount provided to permitted demands. These will be referred to as the Cannabis 1-Month Storage, Cannabis 3-Month Storage, and Cannabis Legal Storage scenarios, respectively. The Unpermitted Junior Priority scenario considers the impact to the system when unpermitted diversions occur at a lower priority than the ecological scenario. This scenario is of interest because it conveys how performance would be affected if all of the unpermitted diverters are brought into compliance and follow the regulations as the eWRIMS diverters are assumed to do. This scenario is referred to as the Cannabis Junior Priority scenario.

The Permitted Water Demands, Reported Water Use scenario uses the maximum reported amounts of demands for each permitted diverter rather than the amount permitted in eWRIMS as in the other scenarios. This scenario is meant to provide a measure to represent how strictly eWRIMS diverters follow allocated diversion limits. This will be referred to as the eWRIMS Reported scenario. The Permitted Water Demands, Storage Off scenario removes off-stream storage for eWRIMS diverters so that the amount of water they are provided is solely based on stream-flow at the time of diversion. This scenario aims to demonstrate to water managers how important having off-stream water storage is to being able to provide water for the various needs. This will be referred to as the eWRIMS Storage Off scenario.

Ecological Scenarios

Fifteen ecological scenarios were developed (Table 4), where each scenario consists of long-term daily stream-flow time series of IFTs at all LOIs. The EPP and Tessmann methods provided IFTs that remained constant across each calendar month, though EPPs differed by WMT (Figure 5). MPOF, POF, and NCIFP scenarios were calculated directly from unimpaired flow, and thus vary over each day of the calendar year. FFM IFTs consist of a single discharge value for the dry and wet season baseflow magnitudes, but these values vary with WYT. Generally, MPOF and the higher POF IFTs had the highest flow targets (Figure 5). However, because they varied based on daily modeled unimpaired flow, they were also lower in drier periods than other IFTs. The lowest EPP scenario, EPP 10, generally had the lowest flow targets at the locations it was developed, but there were days over the simulation period when the EPP targets were greater than unimpaired flow since they are not based on unimpaired flow data.

Table 4 - List and general description of all ecological scenarios used.

Ecological Scenarios	**Description**
EPP (10^{th}, 25^{th}, 50^{th}, 75^{th}, 90^{th}, 100^{th} percentile)	Percentiles of habitat suitability in each water month type in the period of record for juvenile steelhead salmon (Bovee 1982)
Tessmann	Monthly flow targets based on the ratio of mean monthly unimpaired flow to mean annual unimpaired flow (Tessmann 1980).
POF (75%, 80%, 90%, 95%)	Daily flow targets based on a percentage of the total unimpaired flow at each location (Flannery et al., 2002).
MPOF	Monthly diversion limit calculated by taking 10% of the 90th percentile monthly unimpaired flow (Miearu et al., 2017).
NCIFP	Diversion limits that can only occur if daily unimpaired flow is above a certain threshold between December 15 and March 31 (SWRCB 2014).
FFM	Median baseflow magnitude of wet and dry season by water year type (Yarnell et al., 2019; Patterson et al., 2020)
No Criteria	No flow targets are modeled

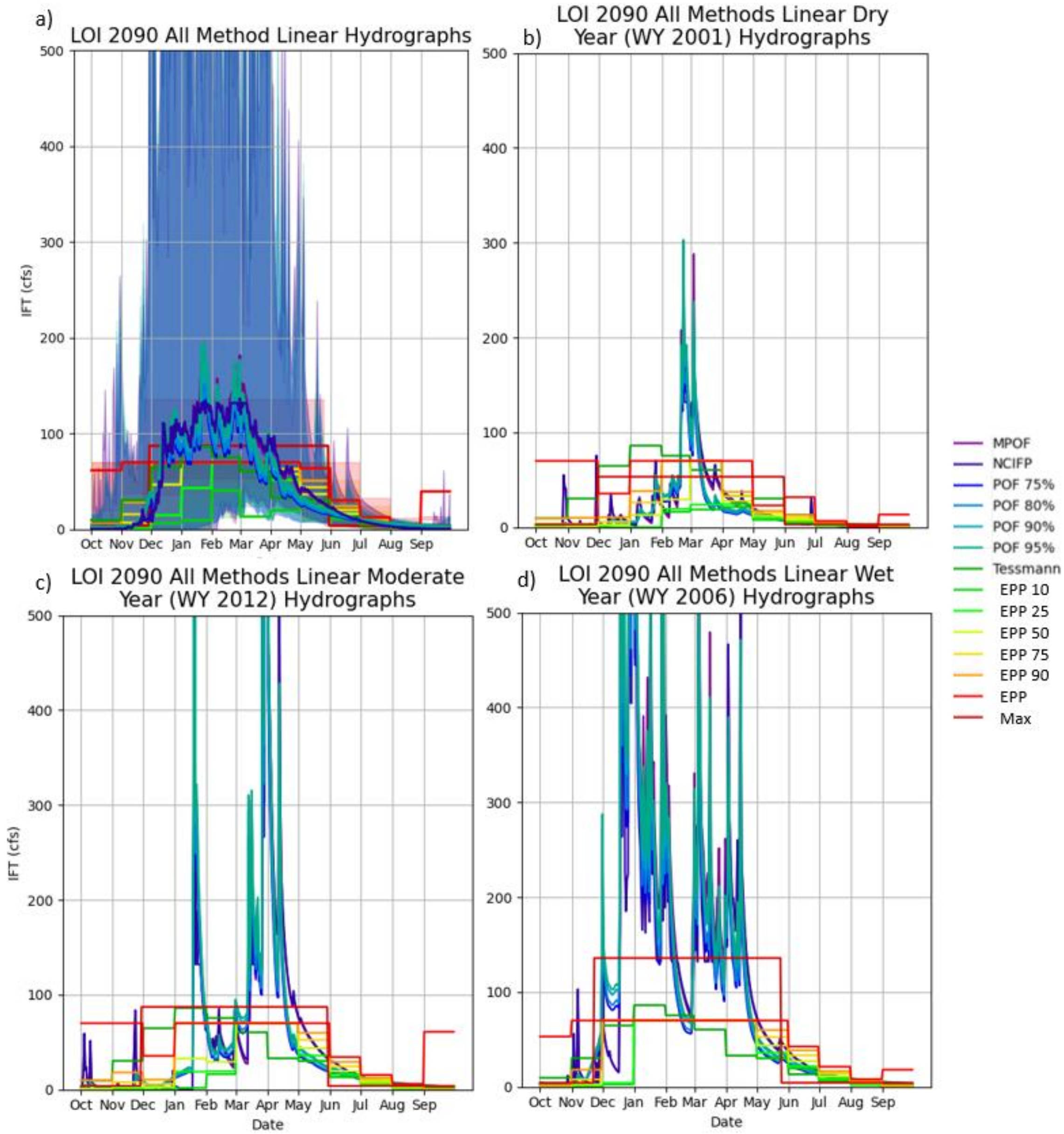


Figure 5 - All IFTs generated for LOI 2090, or the outlet of Redwood Creek. a) Mean IFT values for each day in the year. The transparent solids outside each line correspond to the variability from minimum to maximum IFT for each scenario. Then, specific IFT values are shown in a b) dry, c) moderate, and d) wet year.

Objective 2 –Develop Assessment and Visualization Tool

The dynamic web-based user-interface provides visualizations that evaluate DSS results temporally and spatially for different human and ecological scenarios for watershed stakeholders, here referred to as *dashboards*. The temporal analyses include the ability to filter results by day, month, year, and climate conditions (e.g., dry or wet water months or water years). These analyses aim to provide users with a more complete understanding of the climate-based trends including interannual (e.g., dry years vs. wet years) and annual (e.g., high-flow winters vs. low-flow summers) behavior. Figure 6 shows the first dashboard, which plots permitted water demands in orange and water supplied in blue on the right axis in the top plot. Any two variables can be selected from the top drop-down menu to plot, including human demand, supply, deficit, and volumetric coverage, and flow instream, ecological flow target, flow deficit, and ecological volumetric coverage. The bottom plot shows stream-flow on both linear (blue) and logarithmic (red) scales. The map feature allows users to visualize where and how large the catchment of interest is relative to others.

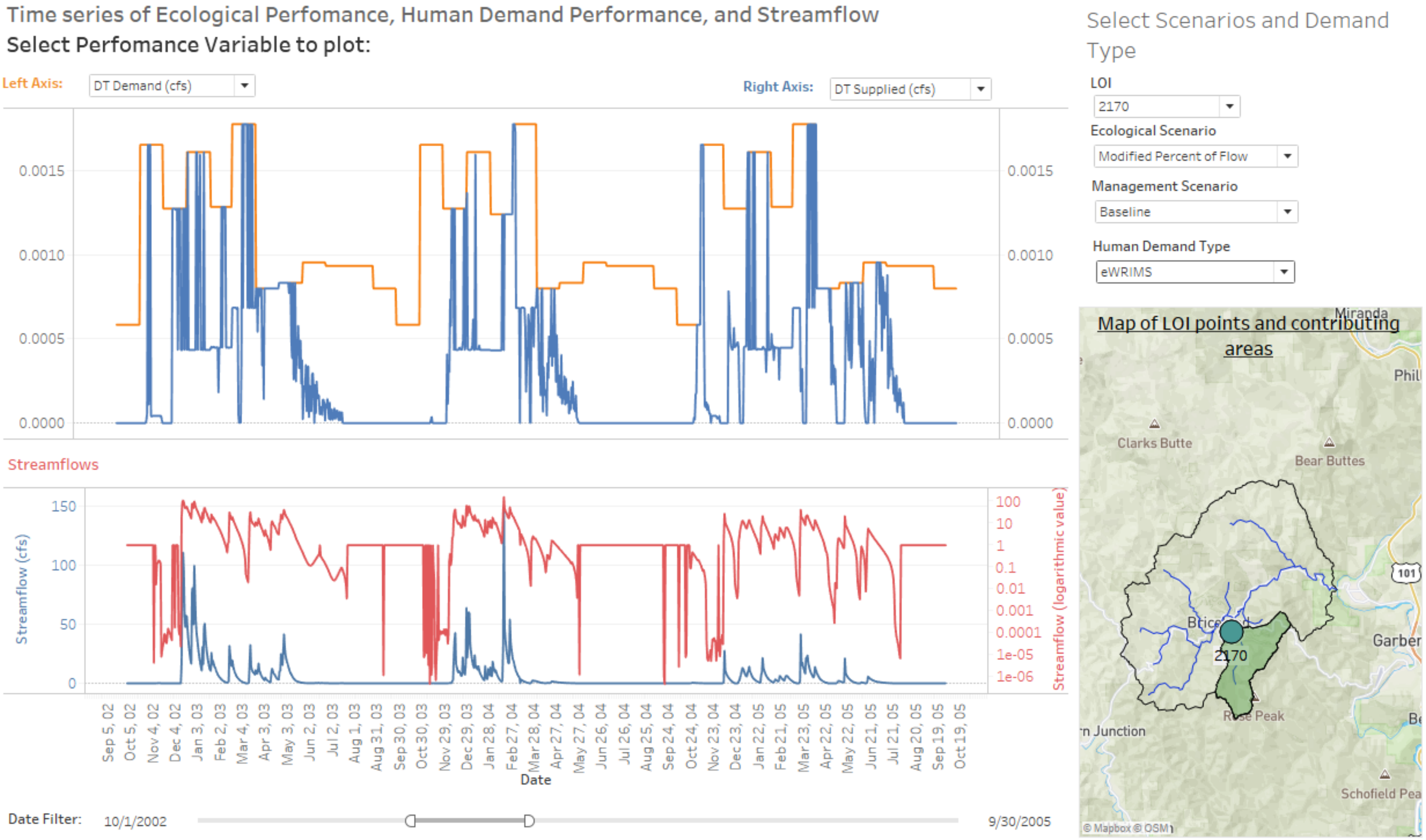


Figure 6 - Example dashboard shows a daily time series of permitted human demands on the left y-axis in orange and the supplied water on the right y-axis in blue (top plot). The lower plot shows total stream-flow throughout the period of record. This data comes from a specific ecological scenario and human scenario and is plotted for a single location.

The next dashboards build on the information in the first dashboard by comparing system performance in different climate conditions with respect to ecological (Figure 7) and human water performance. Boxplots of ecological flow coverage are shown for each water month type, with the distributions in the example scenario clearly shifting upwards with increasing water availability. Each point in the distribution corresponds to a day in the simulation period, and the total number of days in each distribution is shown below the plot. The user also has the option to filter by calendar month so, for example, performance trends can be compared between low-flow and high-flow months.

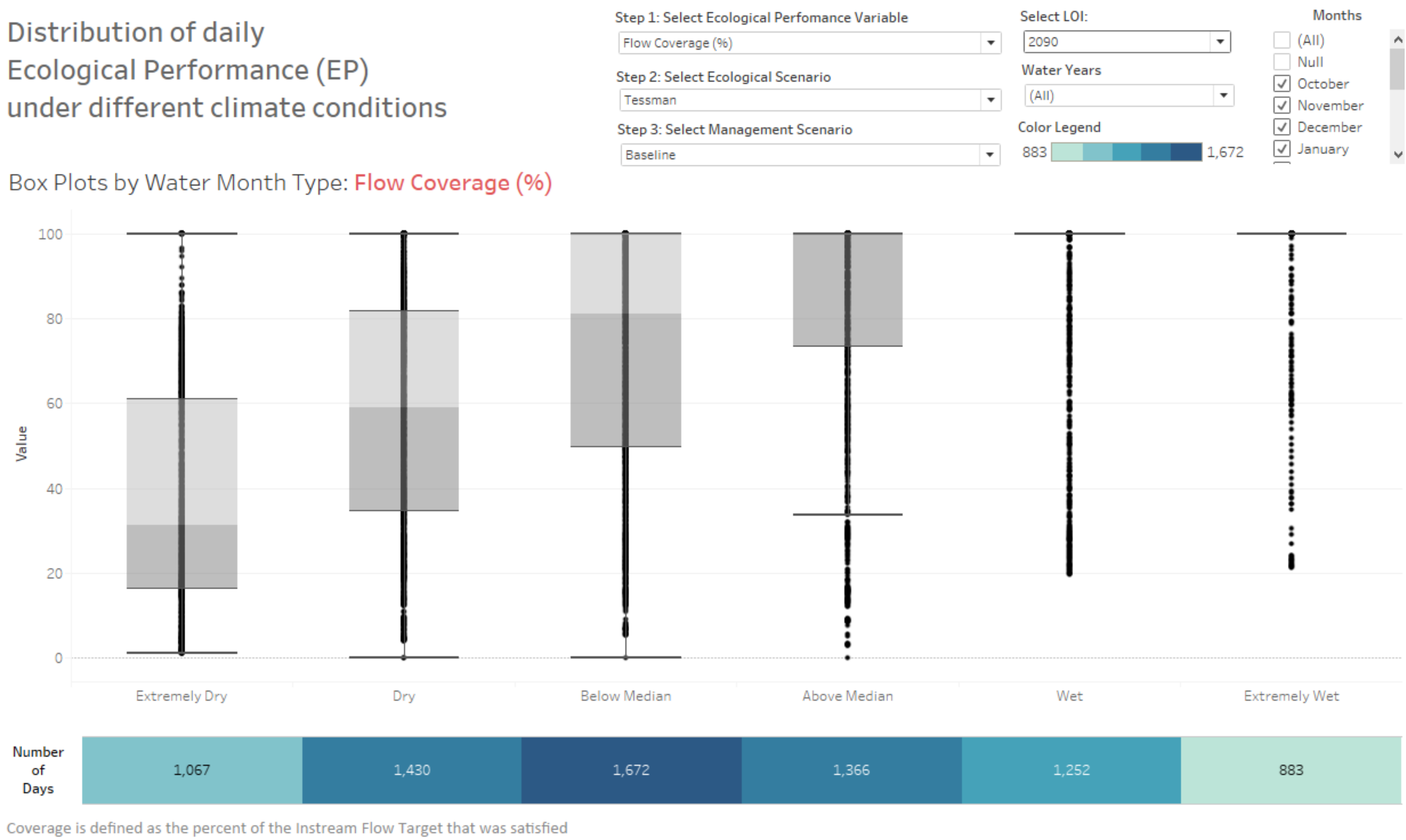


Figure 7 - Example dashboard of ecosystem performance depicted as boxplots of volumetric coverage under different climate conditions (here represented as water month types) over the modeled period of record.

The next dashboard illustrates the mean IFT annual hydrographs for each ecological scenario on a logarithmic scale (Figure 8). Ecological scenario, location, and WMT can be selected to compare IFTs under different conditions. The mean flow value for each day in the POR is plotted since most IFTs vary from year to year depending on the ecological scenario.

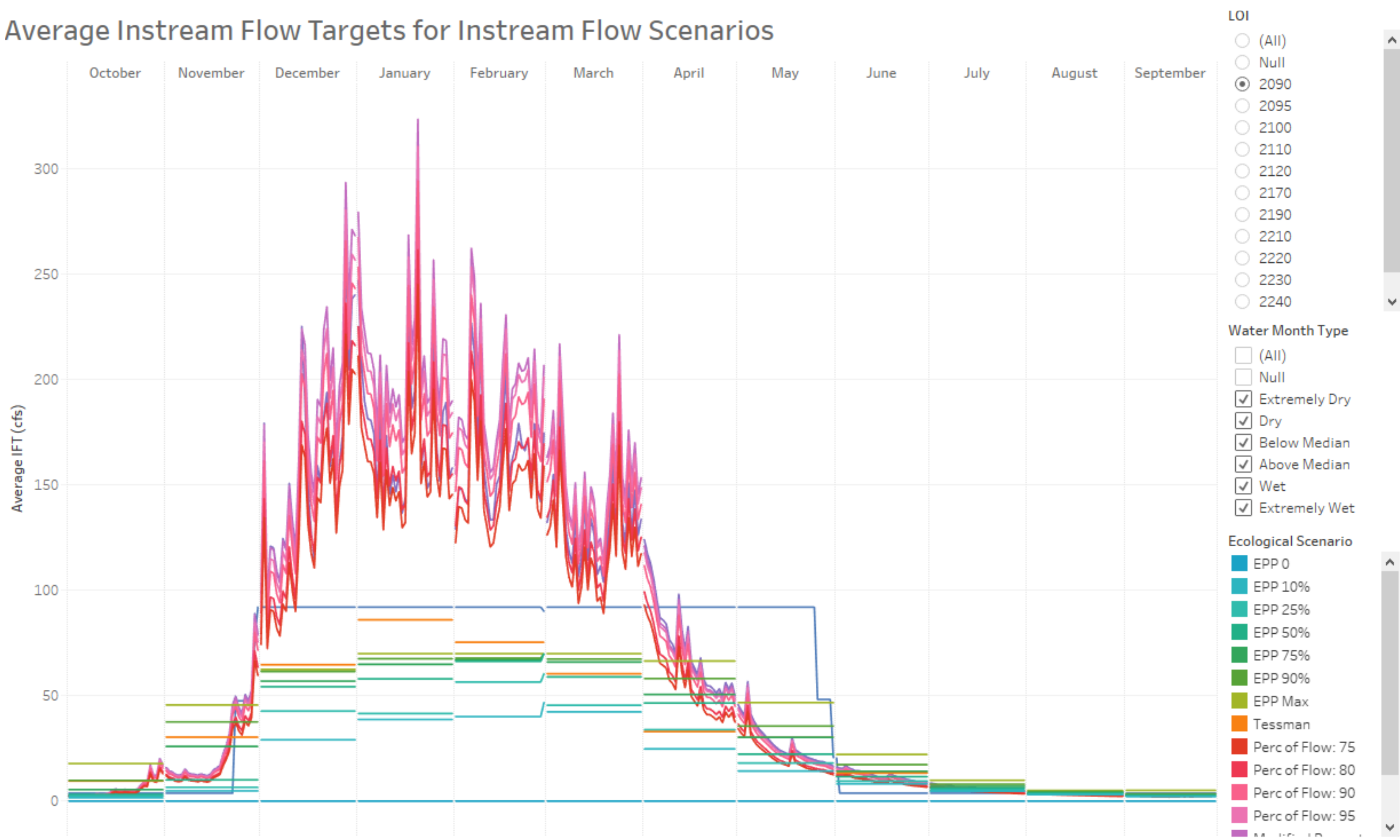


Figure 8 - Example dashboard showing average IFT hydrographs.

The rest of the dashboards present scenario performance comparisons to aid in tradeoff analysis. This has the largest implications for water management decisions since each scenario reflects specific water management decisions or sources of uncertainty with direct implications for system performance. These dashboards include performance tradeoffs in different scenarios (Figure 9), as well as relative performance compared to a baseline scenario (Figure 10) for selected demand types (i.e., human or ecological), locations, and scenarios. There is also an option to change the percent of human demands that need to be met in the assessment of frequency reliability.

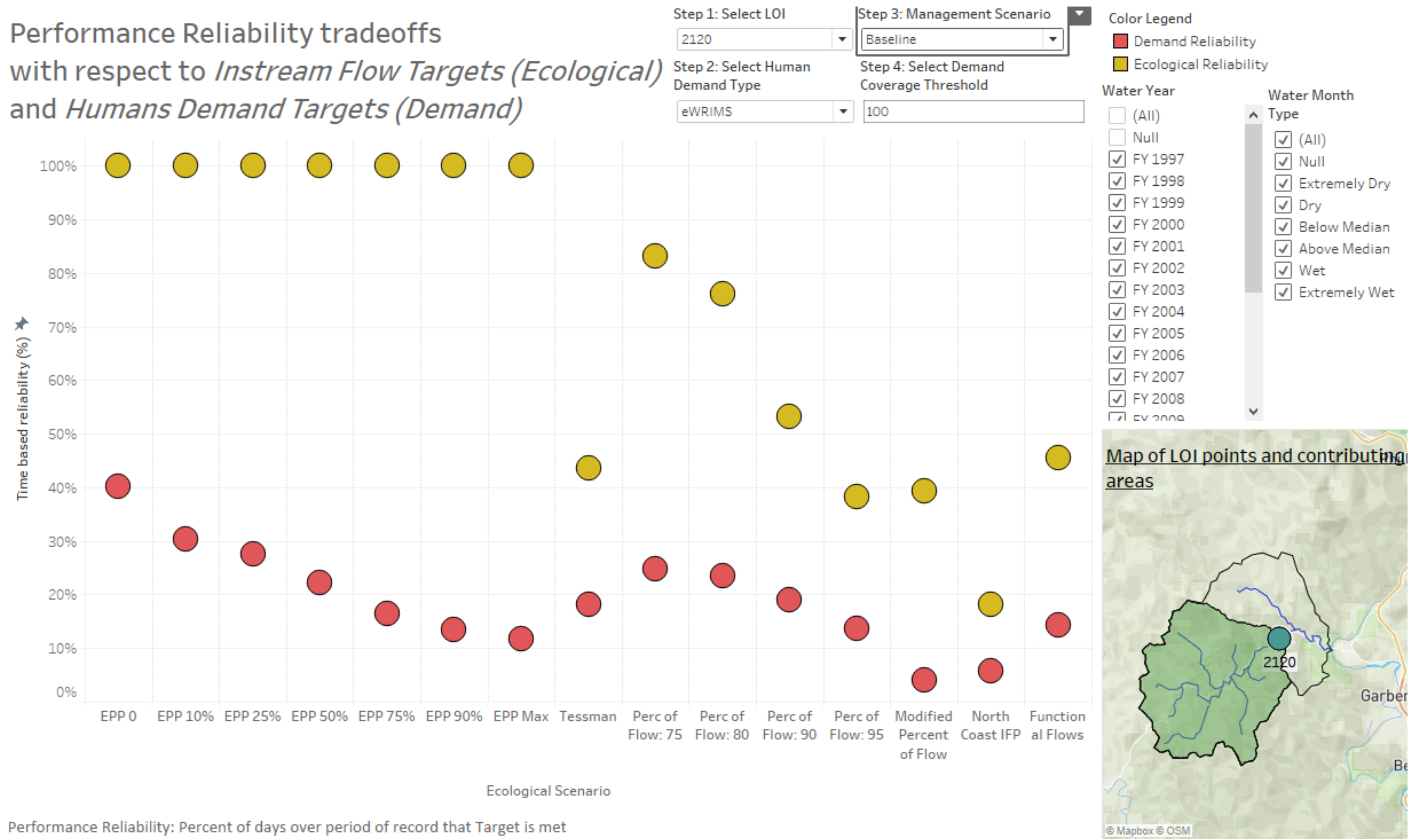
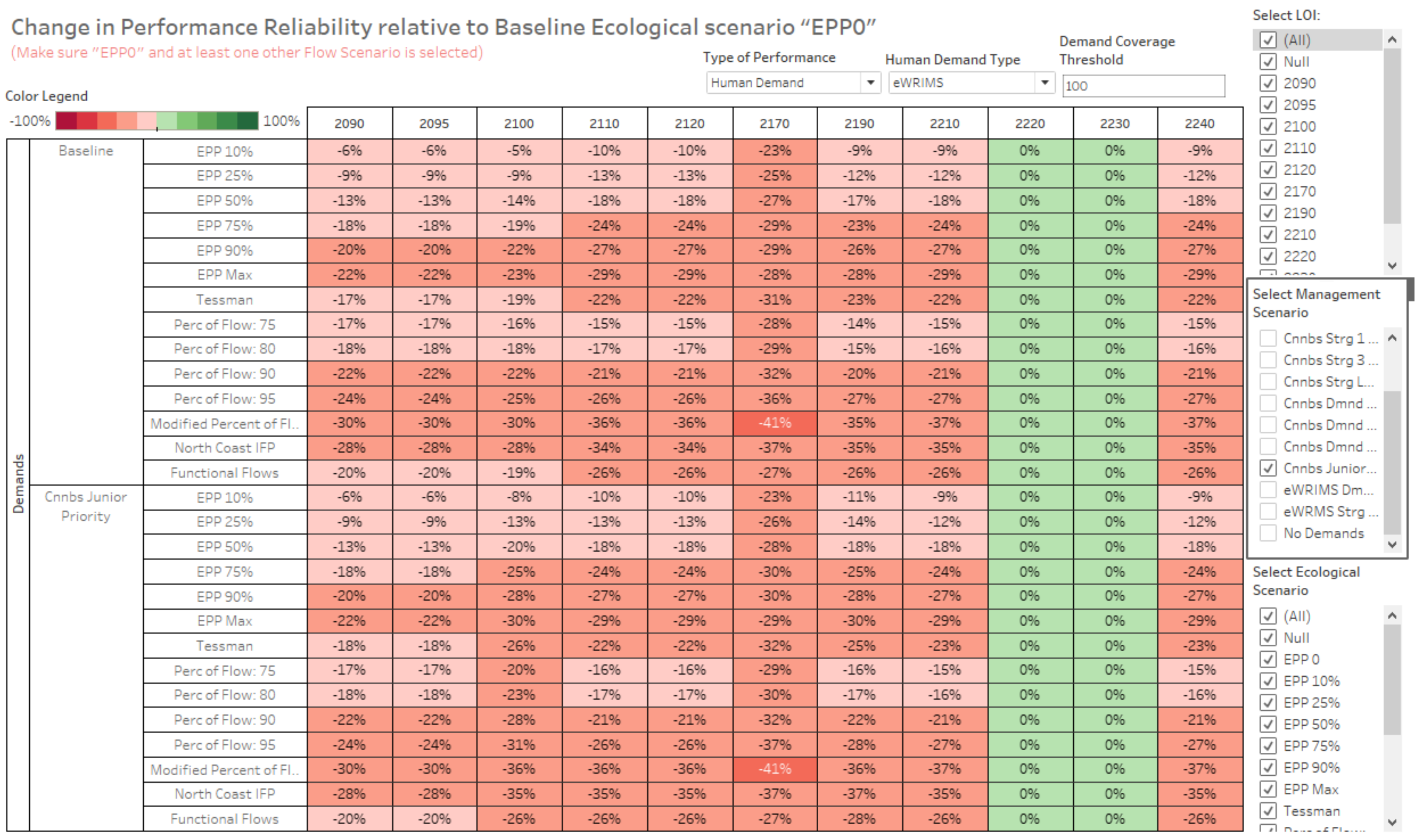


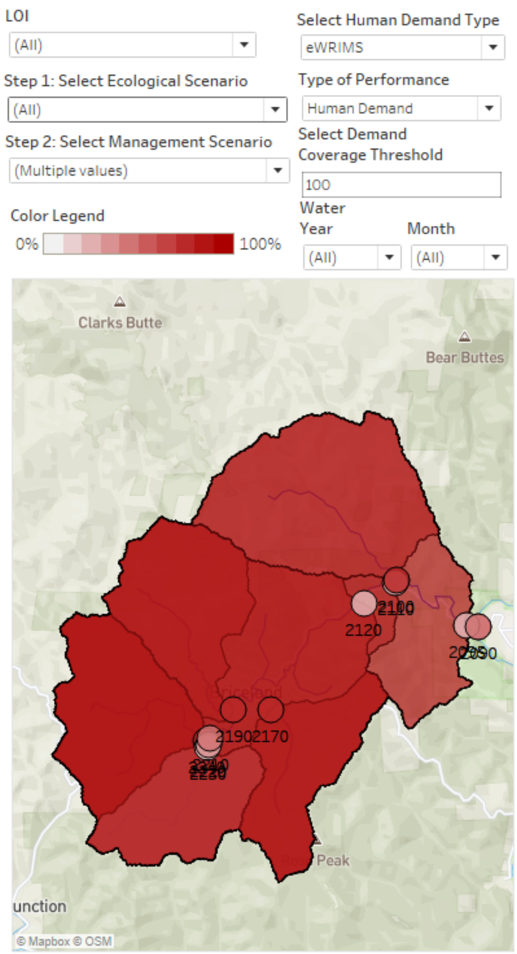
Figure 9 - Example dashboard showing performance in different ecological scenarios for a selected time period and human scenario.



Demands			2090	2095	2100	2110	2120	2170	2190	2210	2220	2230	2240
Demands	Baseline	EPP 10%	-6%	-6%	-5%	-10%	-10%	-23%	-9%	-9%	0%	0%	-9%
		EPP 25%	-9%	-9%	-9%	-13%	-13%	-25%	-12%	-12%	0%	0%	-12%
		EPP 50%	-13%	-13%	-14%	-18%	-18%	-27%	-17%	-18%	0%	0%	-18%
		EPP 75%	-18%	-18%	-19%	-24%	-24%	-29%	-23%	-24%	0%	0%	-24%
		EPP 90%	-20%	-20%	-22%	-27%	-27%	-29%	-26%	-27%	0%	0%	-27%
		EPP Max	-22%	-22%	-23%	-29%	-29%	-28%	-28%	-29%	0%	0%	-29%
		Tessman	-17%	-17%	-19%	-22%	-22%	-31%	-23%	-22%	0%	0%	-22%
		Perc of Flow: 75	-17%	-17%	-16%	-15%	-15%	-28%	-14%	-15%	0%	0%	-15%
		Perc of Flow: 80	-18%	-18%	-18%	-17%	-17%	-29%	-15%	-16%	0%	0%	-16%
		Perc of Flow: 90	-22%	-22%	-22%	-21%	-21%	-32%	-20%	-21%	0%	0%	-21%
		Perc of Flow: 95	-24%	-24%	-25%	-26%	-26%	-36%	-27%	-27%	0%	0%	-27%
		Modified Percent of Fl..	-30%	-30%	-30%	-36%	-36%	-41%	-35%	-37%	0%	0%	-37%
		North Coast IFP	-28%	-28%	-28%	-34%	-34%	-37%	-35%	-35%	0%	0%	-35%
		Functional Flows	-20%	-20%	-19%	-26%	-26%	-27%	-26%	-26%	0%	0%	-26%
	Cnnbs Junior Priority	EPP 10%	-6%	-6%	-8%	-10%	-10%	-23%	-11%	-9%	0%	0%	-9%
		EPP 25%	-9%	-9%	-13%	-13%	-13%	-26%	-14%	-12%	0%	0%	-12%
		EPP 50%	-13%	-13%	-20%	-18%	-18%	-28%	-18%	-18%	0%	0%	-18%
		EPP 75%	-18%	-18%	-25%	-24%	-24%	-30%	-25%	-24%	0%	0%	-24%
		EPP 90%	-20%	-20%	-28%	-27%	-27%	-30%	-28%	-27%	0%	0%	-27%
		EPP Max	-22%	-22%	-30%	-29%	-29%	-29%	-30%	-29%	0%	0%	-29%
		Tessman	-18%	-18%	-26%	-22%	-22%	-32%	-25%	-23%	0%	0%	-23%
		Perc of Flow: 75	-17%	-17%	-20%	-16%	-16%	-29%	-16%	-15%	0%	0%	-15%
		Perc of Flow: 80	-18%	-18%	-23%	-17%	-17%	-30%	-17%	-16%	0%	0%	-16%
		Perc of Flow: 90	-22%	-22%	-28%	-21%	-21%	-32%	-22%	-21%	0%	0%	-21%
		Perc of Flow: 95	-24%	-24%	-31%	-26%	-26%	-37%	-28%	-27%	0%	0%	-27%
		Modified Percent of Fl..	-30%	-30%	-36%	-36%	-36%	-41%	-36%	-37%	0%	0%	-37%
		North Coast IFP	-28%	-28%	-35%	-35%	-35%	-37%	-37%	-35%	0%	0%	-35%
		Functional Flows	-20%	-20%	-26%	-26%	-26%	-27%	-28%	-26%	0%	0%	-26%

Figure 10 - Example dashboard showing relative performance from the ecological scenario with zero flow targets throughout.

The user-interface also provides dashboards that can be used in scenario comparison to show the portion of time human or ecological flow requirements are or are not met by identifying ‘hot spots’ and ‘bright spots’ on the map under different scenarios. ‘Hot spots’ are locations with worse or unacceptable performance (Figure 11), while ‘bright spots’ are high-performing locations under selected scenarios.



Hot Spots: Evaluate Performance Reliability across Ecological and Management scenarios. Indicates percent of time performance does not meet Target

			2090	2095	2100	2110	2120	2170	2190	2210	2220	2230	2240
Demands	Baseline	EPP 0	68%	68%	65%	60%	60%	46%	58%	59%	0%	0%	59%
		EPP 10%	74%	74%	70%	70%	70%	68%	68%	68%	0%	0%	68%
		EPP 25%	77%	77%	74%	72%	72%	71%	70%	71%	0%	0%	71%
		EPP 50%	81%	81%	79%	78%	78%	73%	75%	77%	0%	0%	77%
		EPP 75%	86%	86%	84%	83%	83%	74%	81%	83%	0%	0%	83%
		EPP 90%	88%	88%	87%	87%	87%	75%	84%	86%	0%	0%	86%
		EPP Max	90%	90%	89%	88%	88%	74%	86%	88%	0%	0%	88%
		Tessman	85%	85%	85%	82%	82%	77%	81%	82%	0%	0%	82%
		Perc of Flow: 75	84%	84%	82%	75%	75%	74%	72%	74%	0%	0%	74%
		Perc of Flow: 80	86%	86%	83%	77%	77%	74%	74%	75%	0%	0%	75%
		Perc of Flow: 90	89%	89%	88%	81%	81%	78%	78%	80%	0%	0%	80%
		Perc of Flow: 95	92%	92%	91%	86%	86%	82%	85%	86%	0%	0%	86%
		Modified Percent of Flow	98%	98%	96%	96%	96%	87%	93%	96%	0%	0%	96%
		North Coast IFP	95%	95%	94%	94%	94%	83%	93%	94%	0%	0%	94%
		Functional Flows	87%	87%	85%	86%	86%	72%	84%	85%	0%	0%	85%
	Cnnbs Junior Priority	EPP 0	68%	68%	59%	60%	60%	46%	57%	59%	0%	0%	59%
		EPP 10%	74%	74%	67%	70%	70%	69%	67%	68%	0%	0%	68%
		EPP 25%	77%	77%	72%	72%	72%	72%	70%	71%	0%	0%	71%
		EPP 50%	81%	81%	79%	78%	78%	74%	75%	77%	0%	0%	77%
		EPP 75%	86%	86%	84%	84%	84%	75%	81%	83%	0%	0%	83%
		EPP 90%	88%	88%	87%	86%	86%	75%	84%	86%	0%	0%	86%
		EPP Max	90%	90%	89%	88%	88%	74%	86%	88%	0%	0%	88%
		Tessman	85%	85%	85%	82%	82%	78%	81%	82%	0%	0%	82%
		Perc of Flow: 75	84%	84%	80%	75%	75%	74%	72%	74%	0%	0%	74%
		Perc of Flow: 80	86%	86%	82%	77%	77%	75%	73%	75%	0%	0%	75%
		Perc of Flow: 90	89%	89%	87%	81%	81%	78%	78%	80%	0%	0%	80%
		Perc of Flow: 95	91%	91%	90%	86%	86%	82%	85%	86%	0%	0%	86%
		Modified Percent of Flow	98%	98%	95%	96%	96%	87%	93%	96%	0%	0%	96%
		North Coast IFP	95%	95%	94%	94%	94%	83%	93%	94%	0%	0%	94%
		Functional Flows	87%	87%	85%	86%	86%	72%	84%	85%	0%	0%	85%

Figure 11 – 'Hot spots' of ecological performance for specified human and ecological scenarios across the watershed. The darker the shade of red, the more time spent below an IFT threshold. Human Demand threshold, Ecological threshold, scenario combination, and demand type can be selected in drop-down boxes.

The final dashboards allow for comparison of performance time series (e.g., coverage, deficit, supply, demand, flow, and flow target) across scenarios. There are two dashboards – one that displays multiple ecological scenario results for a single selected human scenario, and one that displays multiple human scenarios for the selected ecological scenario (e.g., 90% POF in Figure 12). These plots allow for quantitative evaluation of how different scenarios alter performance through time as well as how that varies with season or water year type.

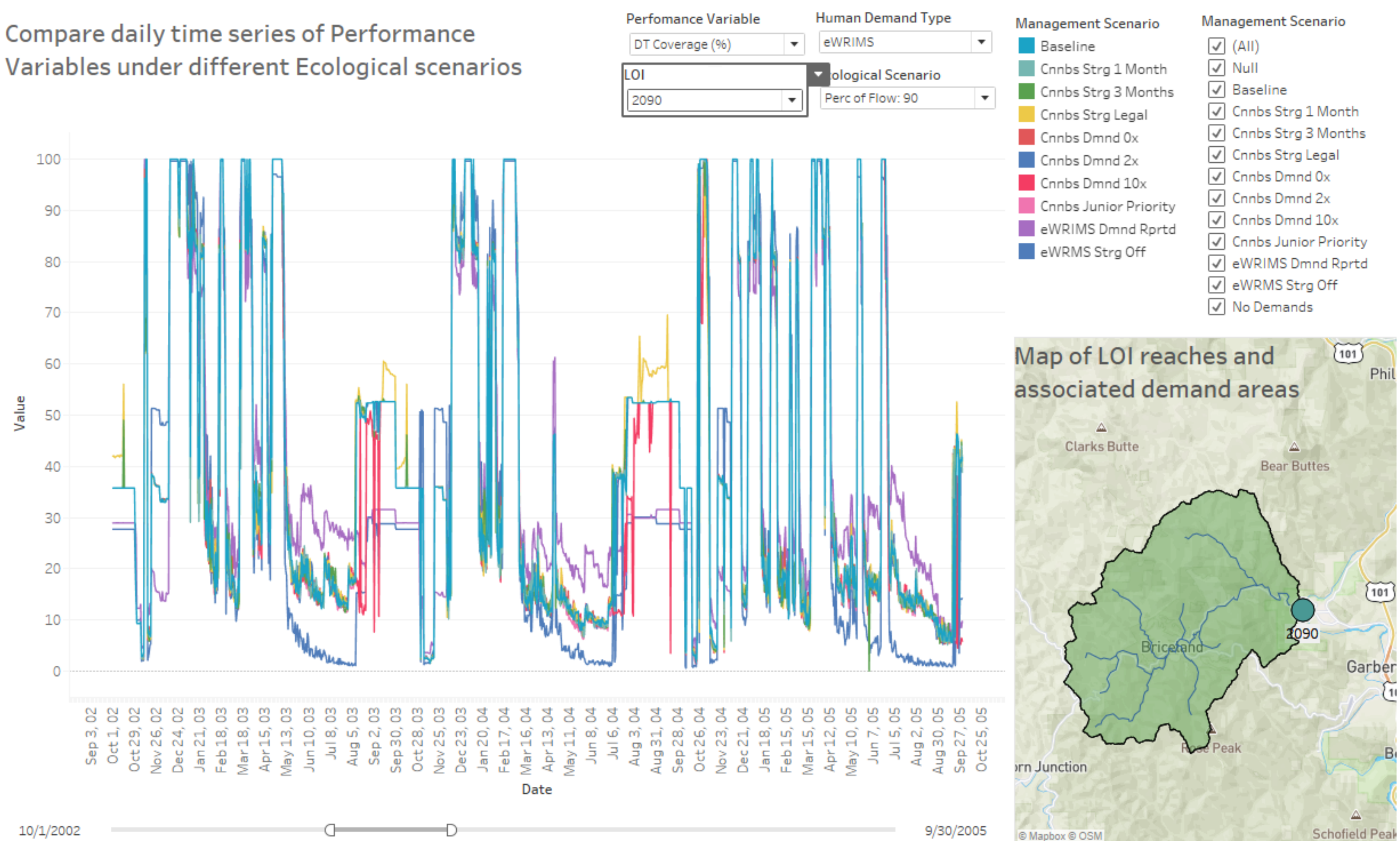


Figure 12 - Example dashboard of the scenario comparison capability.

Objective 3 – Supplemental Scenario Analysis

Reach Setting Parameters

In order to address our research questions, RSP values were calculated for each LOI in the watershed (Table 5).

Table 5 - RSP values for each location in the current SEWAM model. CA stands for Contributing Area, GC stands for Geomorphic Classification, GS stands for Geologic Setting, UDV is the value of upstream demands, UDD is the dominant type of human demands with a U for unpermitted and a P for permitted, UDP is the dominant type of permitted demands, UDA is the upstream demands per unit contributing area, UDM is the upstream demands divided by mean monthly flow, UDL is the upstream demands divided by lowest monthly flow, UDUA is the total unpermitted upstream demands per unit area, UDUM is the total unpermitted upstream demands divided by mean monthly flow, UDUL is the total unpermitted upstream demands per lowest monthly flow, and UDPS is the ratio of unpermitted to permitted human demands in summer months.

LOI	CA (mi^2)	GC	GS	UDV (cfs)	UDD	UDP	UDA (cfs/mi^2)
2220	2.7	SFE05	Yg	2.5E-04	U	Domestic	9.0E-05
2240	3.9	SFE05	Yg	3.4E-02	P	Domestic	8.6E-03
2190	3.7	SFE05	Yg	2.2E-02	P	Irrigation	6.1E-03
2170	2.9	SFE05	Yg	2.1E-03	P	Cannabis (Permitted)	7.3E-04
2100	5.9	SFE05	QTw	3.1E-02	P	Domestic	5.3E-03
2090	26.0	SFE04	QTw	1.3E-01	P	Irrigation	5.0E-03
2230	2.7	SFE05	Yg	2.5E-04	U	Domestic	9.0E-05
2210	6.7	SFE05	Yg	3.4E-02	P	Domestic	5.1E-03
2120	17.2	SFE04	C	7.6E-02	P	Irrigation	4.4E-03
2110	17.6	SFE04	QTw	7.7E-02	P	Domestic	4.4E-03
2095	26.0	SFE04	QTw	1.3E-01	P	Irrigation	5.0E-03
LOI	**UDM**	**UDL**	**UDUA (cfs/mi^2)**	**UDUM**	**UDUL**	**UDPS**	
2220	2.9E-05	0.001	9.0E-05	2.9E-05	0.001	n/a	
2240	4.2E-03	23.529	2.5E-03	1.2E-03	6.794	2.4	
2190	3.0E-03	0.331	2.2E-03	1.1E-03	0.119	2.9	
2170	4.4E-04	0.176	3.5E-04	2.1E-04	0.084	2.3	
2100	4.6E-03	0.062	2.0E-03	1.7E-03	0.023	3.7	
2090	1.9E-03	0.035	1.5E-03	5.4E-04	0.010	1.7	
2230	2.9E-05	0.001	9.0E-05	2.9E-05	0.001	n/a	
2210	2.0E-03	0.113	1.5E-03	5.8E-04	0.033	2.4	
2120	1.5E-03	0.034	1.4E-03	4.9E-04	0.011	2.2	
2110	1.4E-03	0.034	1.4E-03	4.7E-04	0.011	2.2	
2095	1.9E-03	0.036	1.5E-03	5.4E-04	0.010	1.7	

Several RSP values stand out from this table. First, LOIs 2220 and 2230 are very close together, and have no permitted water demands – only unpermitted. The UDPS value is therefore n/a for these locations and they were ignored when analyzing UDPS trends. This is also why these locations are dominated by unpermitted demands as opposed to permitted (UDD). The values for UDL and UDUL at LOI 2240 are approximately 60 times higher than the next highest locations due to the lowest monthly flow at LOI 2240 being near zero. LOI 2240 was therefore not considered when analyzing UDL trends. The small sample size also limits assessment of the importance of Geologic Setting and UDP since the diversity of these settings across the watershed are poorly represented by the 11 locations. For example, LOI 2120 is the only location in Franciscan Central Belt geology.

Several qualitative trends emerged from initial review of Table 5. First, the unpermitted demand RSPs had very similar trends to the total demand RSPs (i.e., UDUA to UDA, UDUL to UDL, and UDUM to UDM), so unpermitted demand RSPs are not discussed in detail. Geomorphic class effectively separately the locations into high CA (for SFE04) and low CA (for SFE05), so trends were highly correlated. Similarly, UDPS generally decreases as CA increases so these performance trends were correlated.

Question 1 – Reach Setting Parameters

Frequency Reliability of Ecological Demands

Ecological frequency reliability generally increases with contributing area (Table 6). This applies in January, July, and over the entire POR (Figure 13 a, b, and c). In general, performance stabilizes at a contributing area threshold which varies by ecological scenario from ~45% – 70%. There is also notable separation between the two geomorphic classes if disregarding the high performance in LOIs 2220 and 2230, with SFE05 locations performing worse than SFE04. Geologic setting is similarly binned, with Franciscan Yager Terrane (Yg) sites exhibiting worse performance. UDA and UDM have similar trends to each other, both generally performing worse at higher values. The trends in UDL were difficult to discern, while UDPS had clear decreasing performance with higher UDPS values (Figure 13 d, e, and f). In general, UDPS, Contributing

Area, and Geomorphic classification had the most consistent trends across all ecological scenarios and times assessed.

Table 6 - Qualitative trends in ecological frequency reliability by RSP over the different times of year. 'Increasing' indicates performance increased with increases in RSP value, 'Decreasing' indicates performance decreased with increases in RSP, 'None' indicates trends could either not be discerned with RSP value or that the value did not significantly change with RSP value, and 'Yes' indicates there were differences in performance between the categories of the categorical RSPs. For the RSPs, CA refers to contributing area, GS refers to Geologic Setting, GC refers to Geomorphic Classification, UDA refers to the upstream demands per unit area, UDL refers to the ratio of upstream demands to lowest monthly flow, UDM refers to the ratio of upstream demands to mean monthly flow, and UDPS refers to the ratio of unpermitted to permitted demands in the summer.

	Entire POR		January		July	
RSP	**MPOF**	**Tessmann**	**MPOF**	**Tessmann**	**MPOF**	**Tessmann**
CA	Increasing	Increasing	Increasing	Increasing	Increasing	Increasing
GS	Yes	Yes	None	None	None	None
GC	Yes	Yes	None	Yes	Yes	Yes
UDA	Decreasing	None	None	None	Decreasing	None
UDL	None	None	None	None	None	None
UDM	Decreasing	None	None	None	Decreasing	None
UDPS	Decreasing	Decreasing	None	Decreasing	Decreasing	Decreasing

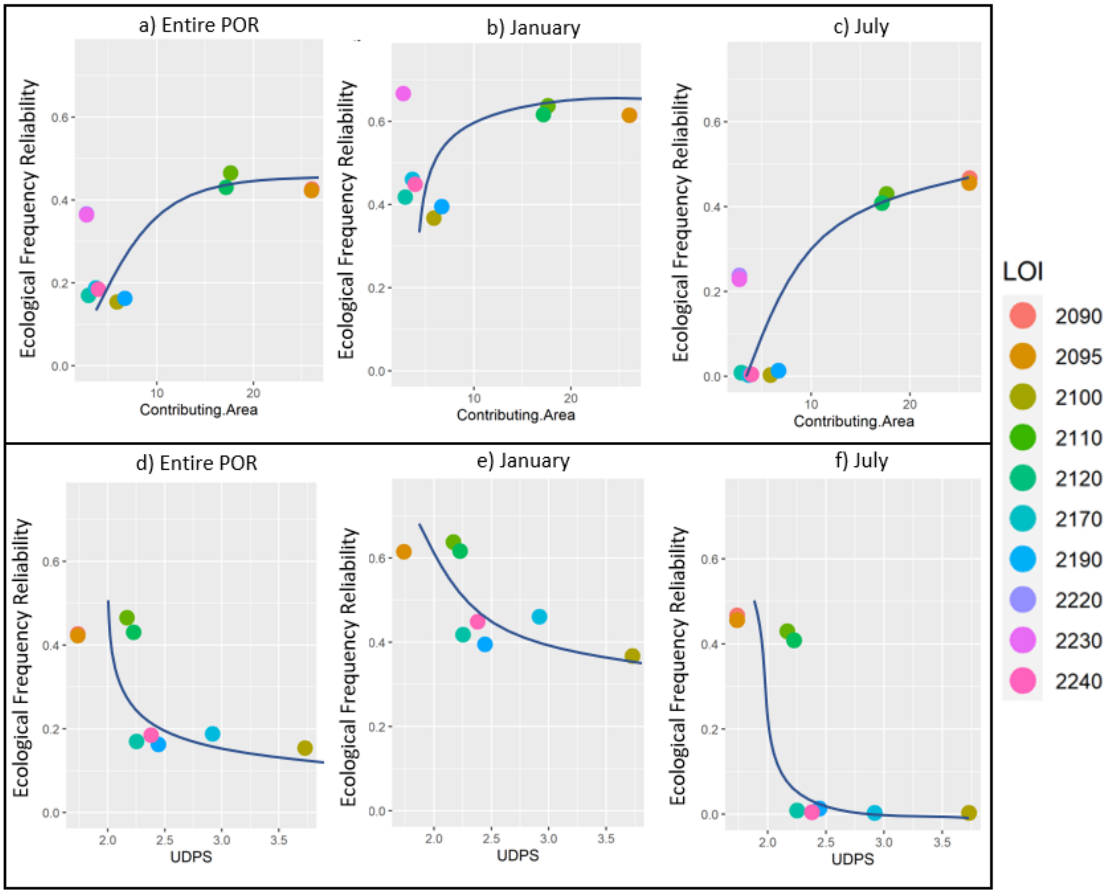


Figure 13 - Qualitative relationships across all model locations in the Tessmann ecological scenario between Ecological Frequency Reliability and Contributing Area over (a) the POR, (b) January, and (c) July, and UDPS in (d) the POR, (e), January, and (f) July.

Frequency Reliability of Human Demands

In general, the frequency reliability of human demands was much lower than the frequency reliability for ecological demands. Most locations have under 10% reliability over the entire POR. Because of this, 50% human frequency reliability was used. In contrast to ecological frequency reliability, performance tends to be lower at larger contributing area locations when looking in January or the entire POR (Table 7). However, July trends are similar to ecological frequency reliability in that they are worse at smaller CA. A decreasing performance trend is more apparent for increases in UDA, UDM, and UDPS. UDL and UDPS have increasing performance with increasing RSP in January, while July had more similar trends to ecological frequency reliability where smaller contributing area locations and locations with higher UDA, UDM, and UDPS had worse performance. There were no significant trends in GS or GC.

Table 7 - Qualitative trends in human frequency reliability by RSP over the different times of year. The terms listed in each cell have the same meaning as outlined in Table 6.

	Entire POR		January		July	
RSP	**MPOF**	**Tessmann**	**MPOF**	**Tessmann**	**MPOF**	**Tessmann**
CA	Decreasing	Decreasing	Decreasing	Decreasing	Increasing	Increasing
GS	None	None	None	None	None	None
GC	None	None	None	None	None	None
UDA	Decreasing	Decreasing	Decreasing	Decreasing	Decreasing	Decreasing
UDL	Increasing	Increasing	Increasing	Increasing	None	Decreasing
UDM	Decreasing	Decreasing	Decreasing	Decreasing	Decreasing	Decreasing
UDPS	Decreasing	Decreasing	Increasing	Increasing	Decreasing	Decreasing

Mean Standardized Impairment (MSI)

Performance trends in MSI were very similar regardless of ecological scenario (Table 8). MSI is very low in January and very high in July which leads to July trends dominating when assessing over the entire POR. The impact of contributing area, geologic setting, and geomorphic classification are not apparent, though demand-based RSPs had clearer increasing trends RSP. UDPS had the clearest trend (Figure 14), followed by UDM, UDA, and UDL. With the current sample size, all of the demand-based RSPs tend to change performance with an exponential relationship, with the higher RSP values increasing MSI much more quickly than lower RSP values.

Table 8- Qualitative trends in MSI by RSP over the different times of year. The terms listed in each cell have the same meaning as outlined in Table 6.

	Entire POR		January		July	
RSP	**MPOF**	**Tessmann**	**MPOF**	**Tessmann**	**MPOF**	**Tessmann**
CA	None	None	None	Increasing	None	None
GS	None	None	None	None	None	None
GC	None	None	None	None	None	None
UDA	Increasing	Increasing	Increasing	Decreasing	Increasing	Increasing
UDL	Increasing	Increasing	Increasing	None	Increasing	Increasing
UDM	Increasing	Increasing	Increasing	Decreasing	Increasing	Increasing
UDPS	Increasing	Increasing	Increasing	Decreasing	Increasing	Increasing

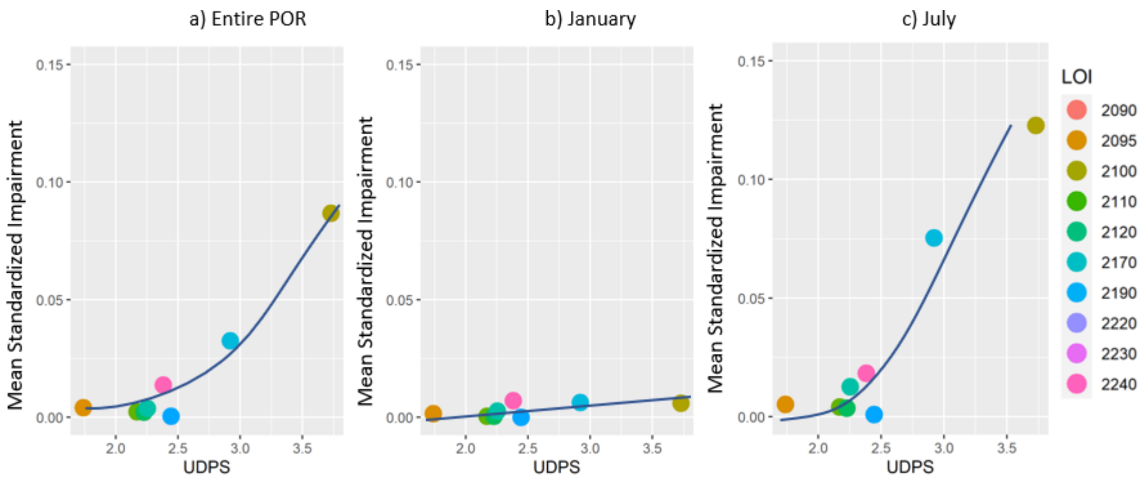


Figure 14 - Qualitative relationships across all model locations in MPOF between MSI and UDPS over (a) the POR, (b) January, and (c) July.

Question 2 – Human Scenarios

Question 2 assesses the impact of the different human scenarios. Question 2a evaluates which human scenarios have the greatest impact on performance relative to baseline, while Question 2b seeks to analyze if the most important human scenarios change with RSP.

Question 2a – Relative Impact of Human scenarios

Frequency Reliability of Ecological Demands

The frequency reliability of ecological demands was most negatively impacted by increasing unpermitted cannabis demands (Figure 15). This was most apparent in the Cannabis Demands 10x scenario, which had the greatest impact across all locations over the entire POR. Conversely, the Cannabis Legal Storage, Cannabis Demands 0x, and Cannabis Junior Priority scenarios had the greatest relative performance increase. The distributions of performance looked similar across these three scenarios, which are henceforth referred to as *positive cannabis scenarios*. For the EPP scenarios, increasing the IFTs to meet higher areal habitat suitability (e.g., EPP 90 and EPP Max) reduced the frequency reliability of meeting these flow targets. Generally, relative performance in January was lower than in July, with unpermitted cannabis storage resulting in a greater reduction in performance than cannabis demands in January (Figure 15b). However, in July the Cannabis Legal Storage scenario had a substantial positive effect on performance, even more so than Cannabis Demands 0x and Cannabis Junior Priority (Figure 15c).

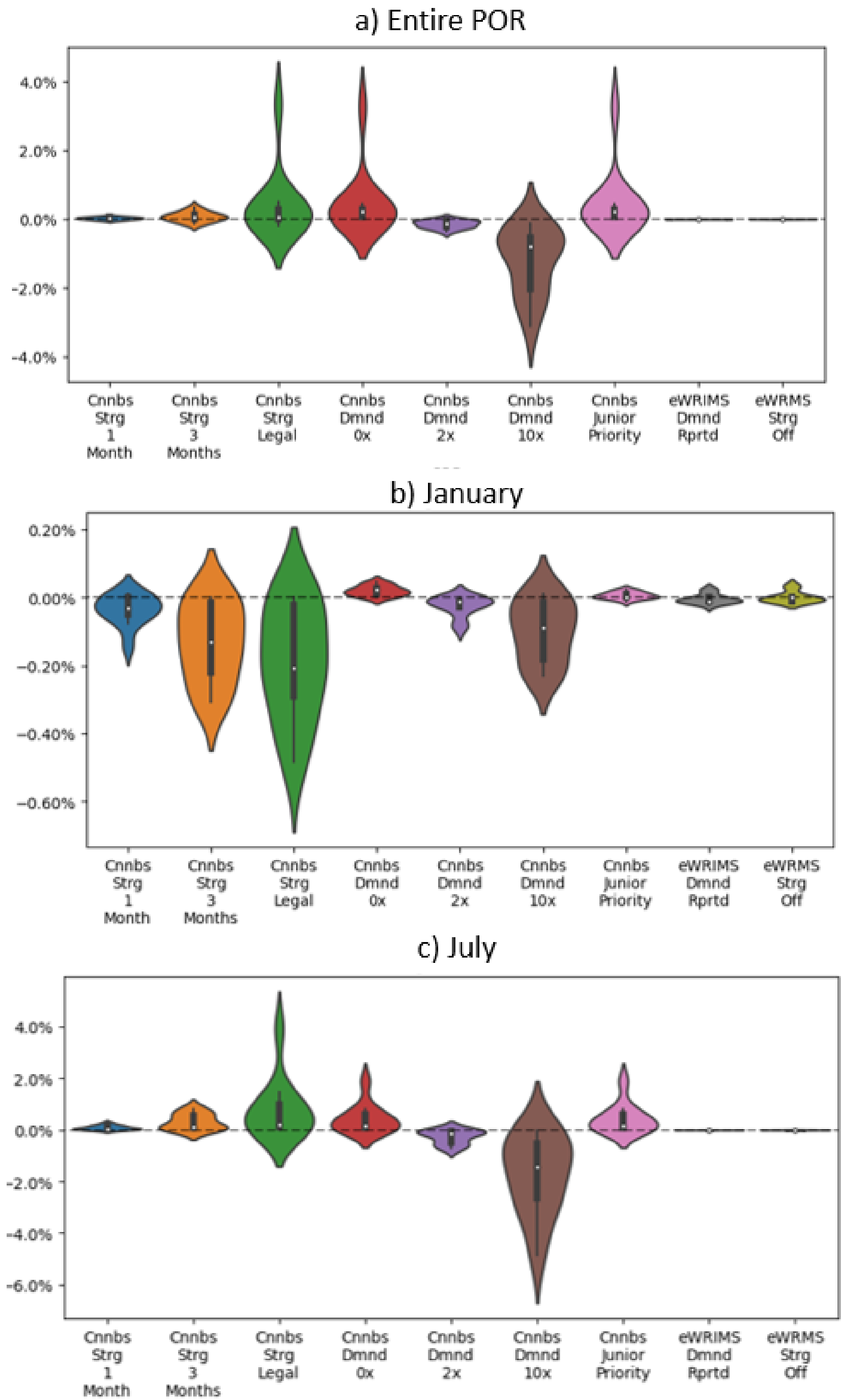


Figure 15 – Violin plots of relative performance in ecological frequency reliability for each human scenario across all years and ecological scenarios in (a) the POR, (b) January, and (c) July.

Frequency Reliability of Human Demands

Unlike ecological frequency reliability, human frequency reliability is mostly impacted by human scenarios that affect the permitted demands as opposed to the unpermitted demands. eWRIMS Reported had the most positive distribution of relative performance, even though some locations are negative due to having more reported demands than permitted. On the other end, removing storage for permitted demands (eWRIMS Storage Off scenario) had the largest negative relative performance (Figure 16a). Cannabis Demands 10x also had a negative impact, but not as much as eWRIMS Storage Off. In MPOF, both the eWRIMS Reported scenario and the eWRIMS Storage Off scenario actually have a positive relative performance, with the mean of relative performance in the eWRIMS Storage Off scenario being higher than the eWRIMS Reported scenario. The eWRIMS Storage Off scenario has positive relative performance in January (Figure 16b), but very negative relative performance in July (Figure 16c). The Cannabis Demands 10x has similar values to the eWRIMS Storage Off scenario in July, with eWRIMS Reported having almost no effect. Though the distribution of locations looks similar across ecological scenarios, the box and whiskers are more negative in lower IFTs.

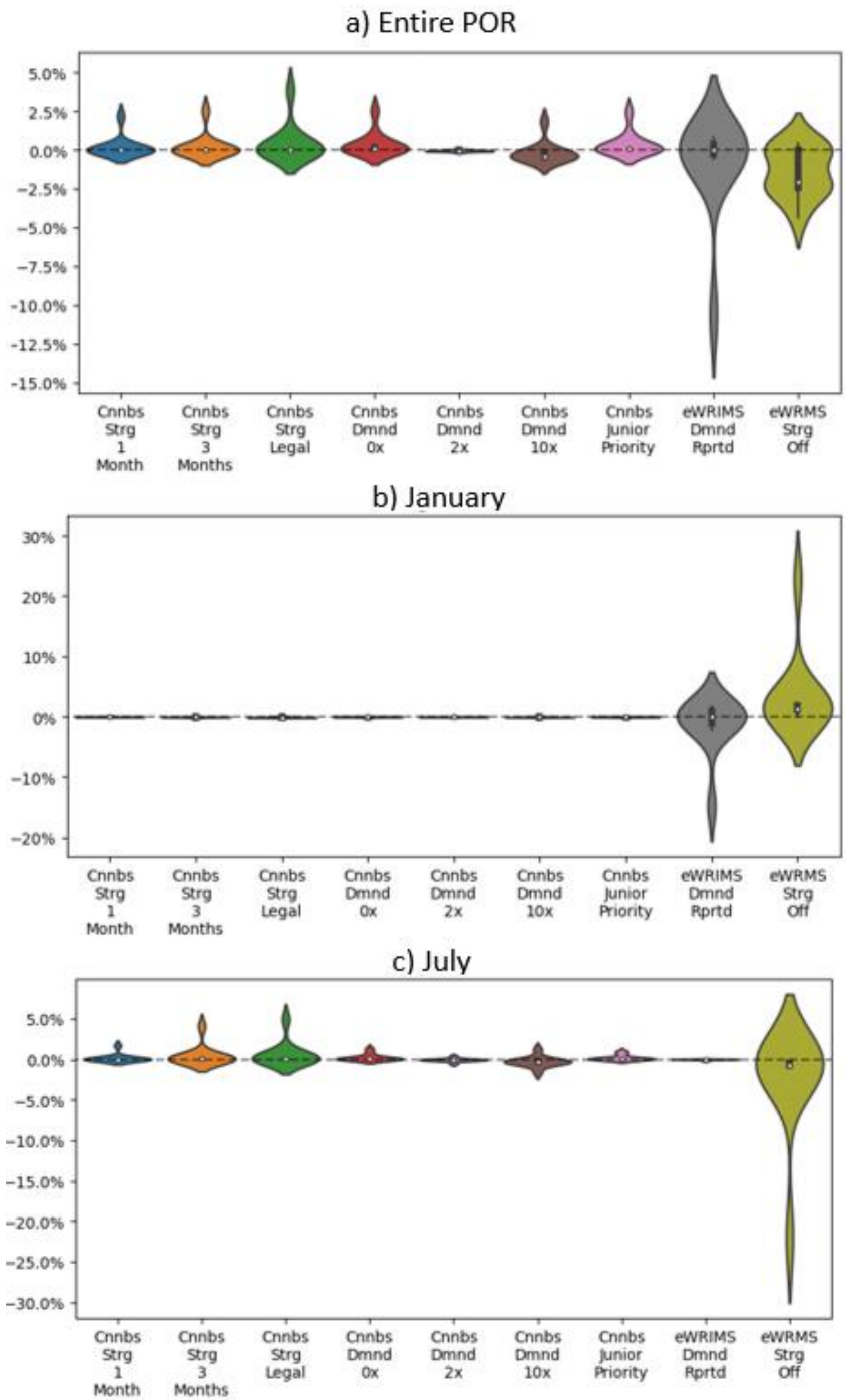


Figure 16 - Relative performance distributions in human frequency reliability in each of the human scenarios for the average across all ecological scenarios in (a) the POR, (b) January, and (c) July.

Mean Standardized Impairment (MSI)

When analyzing MSI over the entire POR, the positive cannabis scenarios had similar negative distributions, with Cannabis Demands 0x and Cannabis Junior Priority being the most similar. Cannabis Demands 10x had a greater magnitude of relative performance than the positive cannabis scenarios, only in the positive relative performance direction (i.e., a net increase in MSI). Relative performance of MSI was not heavily impacted by the ecological scenario. Relative performance in January had much smaller magnitudes than July, with January MSI increasing the most when unpermitted cannabis storage was added. eWRIMS Storage Off has a more positive relative performance in July than compared to the entire POR, though much less substantial than Cannabis Demands 10x.

Question 2b – Relative Impact of Human scenarios by RSP

Frequency Reliability of Ecological Demands

Over the entire POR, there were some changes based on geomorphic classification and geologic setting – specifically, locations in geomorphic class SFE04 and geologic setting QTw had higher relative performance across human scenarios (Table 9). For contributing area, the Cannabis Demands 10x scenario has the greatest negative impact overall, with larger contributing area locations impacted the most (Figure 17a). Similarly, Cannabis Demands 10x has a greater negative impact at larger UDA locations (Figure 17c). The scenarios with the greatest positive impact were the positive cannabis scenarios, with Cannabis Demands 0x and Cannabis Junior Priority being very similar. For UDA, UDL, and UDM, lower RSP values have similarly positive relative performance in the three positive cannabis scenarios. Though, at higher RSP values of these three metrics, Cannabis Demands 0x and Junior Priority become more important. For UDL, all human scenarios become less important at higher values. UDPS has the same trends for

Cannabis Demands 10x where higher UDPS values approach zero, but the positive cannabis scenarios have a much greater positive impact at higher UDPS (Figure 17e).

Table 9 - Qualitative trends in relative performance of ecological frequency reliability against different RSPs of human scenarios with significant values of relative performance. 'Increasing' indicates the scenario had a higher magnitude (whether positive or negative) of relative performance at higher RSP locations, 'Decreasing' indicates the scenario had a lower magnitude of relative performance at higher RSP locations, and 'Flat' indicates there was no significant change over the different RSP values. For categorical RSPs, 'None' indicates there were no significant changes in relative performance between the different categories, and 'Yes' indicates there were different values of relative performance between categories with 'Slight' indicating slightly, but not significantly different values.

	Entire POR			**January**		
RSP	**Cann 0x/Junior**	**Cann Legal Strg**	**Cann Dem 10x**	**Cann 0x/Junior**	**Cann Legal Strg**	**Cann Dem 10x**
CA	Decreasing	Increasing	Increasing	Flat	Increasing	Flat
GS	Yes, Slight	Yes	Yes	None	None	None
GC	Yes, Slight	Yes, Slight	Yes	None	None	None
UDA	Increasing	Increasing	Increasing	Flat	Increasing	Increasing
UDL	Decreasing	Decreasing	Decreasing	Flat	Increasing	Increasing
UDM	Increasing	Increasing	Flat	Flat	Increasing	Increasing
UDPS	Increasing	Increasing	Decreasing	Flat	Increasing	Increasing
	July					
	Cann 0x/Junior	**Cann Legal Strg**	**Cann Dem 10x**			
CA	Increasing	Increasing	Increasing			
GS	Yes, Slight	Yes	Yes			
GC	Yes	Yes	Yes			
UDA	Increasing	Increasing	Increasing			
UDL	Decreasing	Decreasing	Decreasing			
UDM	Increasing	Increasing	Flat			
UDPS	Increasing	Increasing	Decreasing			

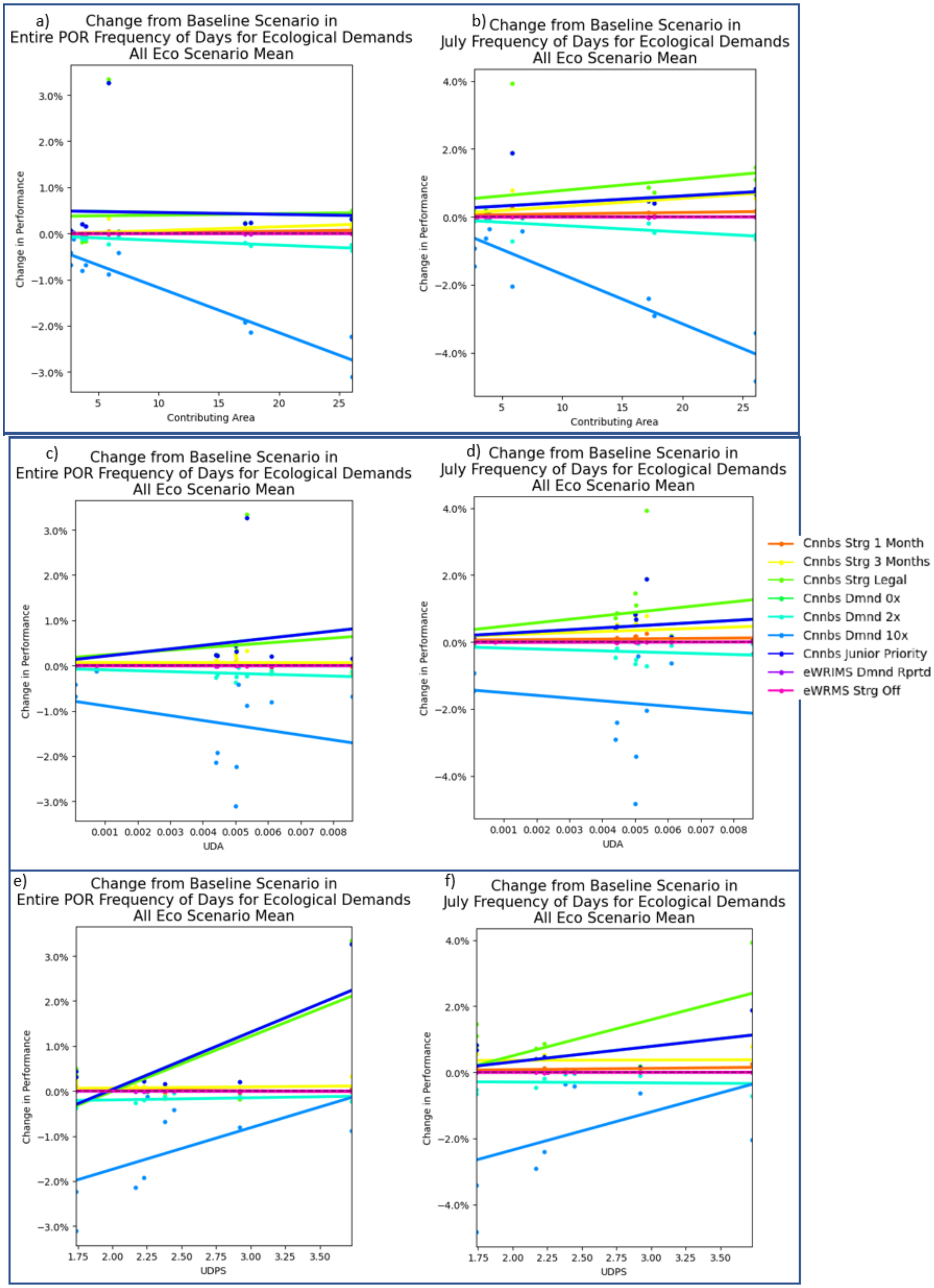


Figure 17 - Changes in mean relative performance of ecological frequency reliability across all ecological scenarios by RSP over the entire POR and July for Contributing Area (a and b), UDA (c and d), and UDPS (e and f).

In January, Cannabis 3-Month and Cannabis Legal Storage become more important at larger CA, with both having more negative relative performance than Cannabis Demands 10x at these locations. The trends in UDA, UDL, UDM, and UDPS in January also show cannabis storage being much more important at higher RSP values, only here both storage parameters have little to no effect at lower RSP values. In July, unpermitted cannabis storage becomes more important than controlling unpermitted cannabis demands, with the Cannabis 3-Month Storage scenario having a similar positive relative performance as Cannabis Demands 0x and Cannabis Junior Priority, and Cannabis Legal Storage being much greater. The impact of these storage scenarios in July is much more substantial and increases with contributing area, UDA, UDM, and UDPS, leaving UDL as the only RSP that has a decreasing relationship with relative performance (Figure 17b, d, and f). Cannabis Demands 10x is roughly flat with UDA and UDM in July, increasing in importance with CA and UDA, and decreasing in importance with UDL and UDPS.

Frequency Reliability of Human Demands

As discussed above, the relative frequency reliability of human demands was most negatively impacted by the eWRIMS Storage Off and eWRIMS Reported scenarios (Table 10). The eWRIMS Storage Off scenario has a greater impact at lower UDA, UDM, and UDPS, and at higher UDL locations with no strong trend in CA, while eWRIMS Reported has similar trends except is more impactful at smaller CA. The positive cannabis scenarios have the most positive relative performance values, though at a much smaller magnitude than the eWRIMS Reported/Storage Off scenarios. These three scenarios are more important in small CA, UDA, and UDM locations, and more important in larger UDL and UDPS locations. In contrast to all the other ecological scenarios, MPOF saw positive relative performance values for eWRIMS Storage Off and eWRIMS Reported.

eWRIMS Storage Off was similarly the most important when looking at either the wet or dry season. In January, eWRIMS Storage Off has a positive relative performance with a greater impact at smaller CA, UDA, and UDM locations and at larger UDL locations, with an unchanging relationship by UDPS. eWRIMS Reported had similar trends, only with negative values. MPOF is the exception to this, with eWRIMS Reported having positive relative performance across all locations (though with a smaller magnitude than eWRIMS Storage Off) in MPOF. July similarly showed eWRIMS Storage Off having the greatest impact at lower UDA, UDM, and UDPS, and higher UDL. Comparatively, eWRIMS Reported had almost no effect on relative performance regardless of RSP. However, it has the greatest impact at lower CA. Cannabis Demands 10x becomes more important in July, having similar trends as eWRIMS Storage Off though with a smaller magnitude. As in other analyses of July performance, the Cannabis Legal Storage scenario is more important at smaller CA, and larger UDA, UDL, UDM, and UDPS, with Cannabis Demands 0x and Junior Priority having similar qualitative trends at a smaller impact.

Table 10- Qualitative trends in relative performance of human frequency reliability against different RSPs of human scenarios with significant values of relative performance. The terms have the same meaning as listed in Table 9.

	Entire POR			January	
RSP	**eWRIMS Rep**	**eWRIMS Strg Off**	**Cann 0x/ Junior/ Leg Strg**	**eWRIMS Rep**	**eWRIMS Strg Off**
CA	Decreasing	Increasing	Decreasing	Decreasing	Decreasing
GS	None	None	None	None	None
GC	None	None	None	Yes, Slight	None
UDA	Decreasing	Decreasing	Decreasing	Decreasing	Decreasing
UDL	Increasing	Increasing	Increasing	Increasing	Increasing
UDM	Decreasing	Decreasing	Decreasing	Decreasing	Decreasing
UDPS	Decreasing	Decreasing	Increasing	Decreasing	Flat
	July				
	eWRIMS Strg Off	**Cann Dem 10x**	**Cann Legal Strg**		
CA	Increasing	Flat	Decreasing		
GS	None	None	None		
GC	None	None	None		
UDA	Increasing	Increasing	Increasing		
UDL	Increasing	Increasing	Flat		
UDM	Increasing	Increasing	Increasing		
UDPS	Flat	Increasing	Increasing		

Mean Standardized Impairment (MSI)

Qualitative RSP trends in MSI do not differ significantly between ecological scenarios. Relative performance was most positive in Cannabis Demands 10x, with greater magnitudes at larger demand-based RSPs and not much change by CA (Figure 18). The positive cannabis storage scenarios drove the largest decrease in performance, with larger impacts at smaller contributing areas and larger demand-based RSPs (Table 11). Though in January, Cannabis Legal Storage had a larger positive magnitude than Cannabis Demands 10x at higher demand-based RSPs and lower CA. eWRIMS Reported has the most negative impact in January, but is relatively similar to the eWRIMS Storage Off scenario in terms of negative relative MSI. Cannabis Demands 10x performance was insensitive to CA, UDA, and UDM, and increased with UDL and

UDPS in July. In terms of decreasing MSI performance, the three positive cannabis scenarios have a greater negative magnitude at low contributing areas and high demand-based RSPs, with a strong decreasing trend in UDPS. The Cannabis 3-Month Storage scenario has similar relative performance in July as Cannabis Demands 10x at higher UDL, UDA, and UDPS values, only in the negative direction.

Table 11 - Qualitative trends in relative performance of MSI against different RSPs of human scenarios with significant values of relative performance. The terms have the same meaning as listed in Table 9.

	Entire POR		**January**		
RSP	**Cann 0x/ Junior/ Leg Strg**	**Cann Dem 10x**	**Cann 0x/ Junior**	**Cann Legal Strg**	**Cann Dem 10x**
CA	Decreasing	Flat	Flat	Decreasing	Decreasing
GS	None	None	None	None	None
GC	None	None	None	None	None
UDA	Increasing	Increasing	Flat	Increasing	Increasing
UDL	Increasing	Increasing	Increasing	Increasing	Increasing
UDM	Increasing	Increasing	Flat	Increasing	Increasing
UDPS	Increasing	Increasing	Flat	Increasing	Increasing
	July				
	Cann 0x/ Junior/ Leg Strg	**Cann Dem 10x**			
CA	Decreasing	Flat			
GS	None	None			
GC	None	None			
UDA	Increasing	Flat			
UDL	Increasing	Increasing			
UDM	Increasing	Flat			
UDPS	Increasing	Increasing			

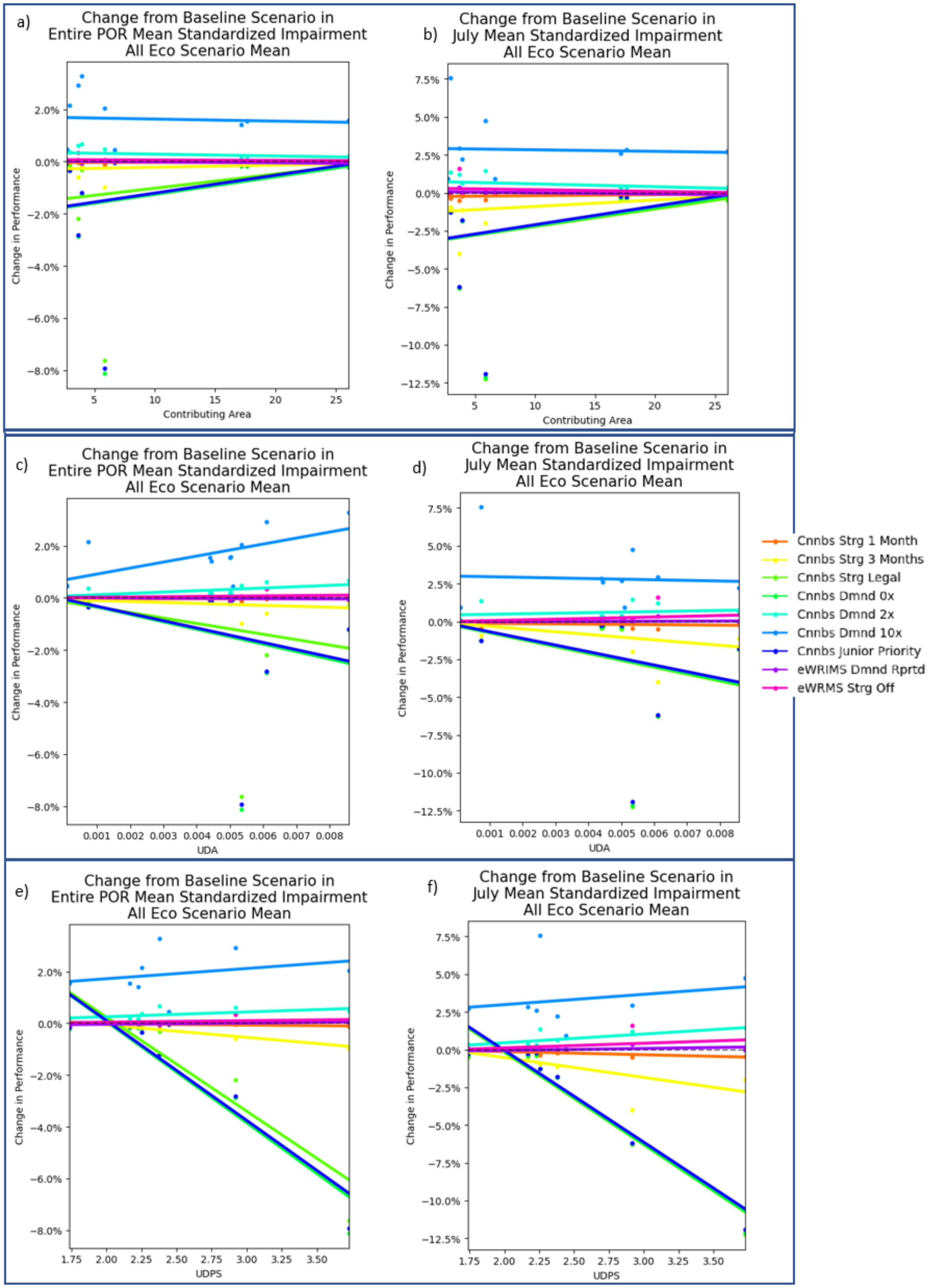


Figure 18 - Changes in mean relative performance of MSI across all ecological scenarios by RSP over the entire POR and July for Contributing Area (a and b), UDA (c and d), and UDPS (e and f).

Question 3 – Climate

Frequency Reliability of Ecological Demands

When looking at each calendar month, LOI 2090 had variable ecological frequency reliability in the dry season, with EPP 10 and POF 75% performing best and EPP Max performing very poorly. Meanwhile, LOI 2240 performed very poorly in the dry season, with 0% performance in August in all human and ecological scenarios (Figure 19, Figure 20). Human scenario had almost no impact at LOI 2240, while at LOI 2090 the scenario had a large effect on dry season performance between the human scenarios. At both locations, MPOF flow targets were met the least frequently of all ecological scenarios. The lower EPP scenarios and POF scenarios have the best performance in the wet season, with POF scenarios performing better in the dry months at LOI 2090. MPOF, POF 95%, and NCIFP have the worst performance over the wet season, while the higher EPPs have worse performance in the dry season. When comparing performance in July alone, Cannabis Demands 10x had a much larger impact than in other temporal aggregations, with up to a 25% difference between the best (Cannabis Legal Storage) and the worst (Cannabis Demands 10x) performing scenarios. Cannabis Legal Storage makes the biggest difference in POF 90%, 95%, MPOF, and NCIFP scenario.

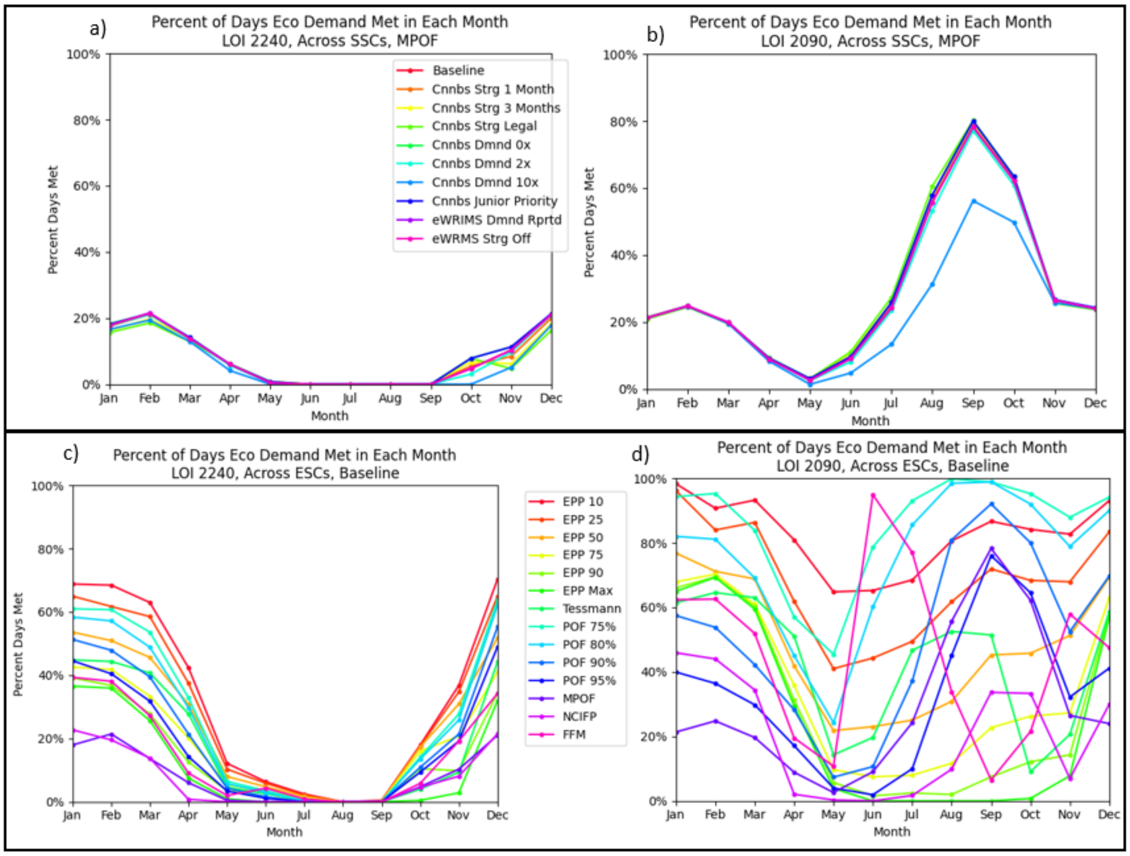


Figure 19 – Ecological frequency reliability in each month at LOI 2240 and LOI 2090 in MPOF across all human scenarios (a and b) and in the Baseline human scenario across all ecological scenario (c and d).

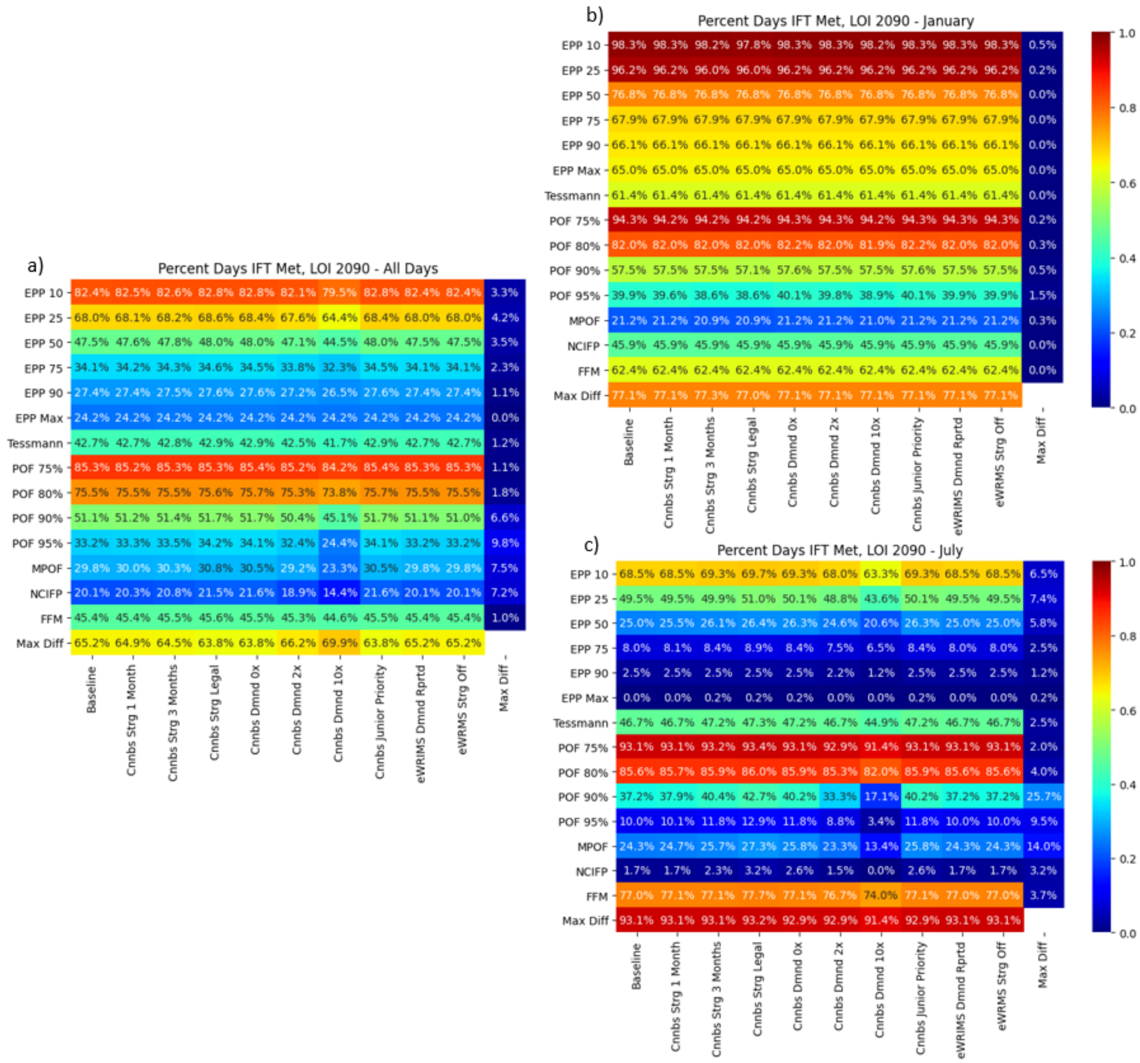


Figure 20 - Ecological frequency reliability at LOI 2090 by every scenario combination in a) the POR, b) Januarys, and c) Julys. The 'Max Diff' row and column show the difference between the highest value and the lowest value of performance in each column and row, respectively.

When looking at interannual variability introduced by WMT, there is not much variation between human scenarios besides Cannabis Demands 10x at either location. Cannabis Demands 10x has a greater separation from the other human demand scenarios in drier WMTs at both locations, with the greatest separation occurring when MPOF is implemented. The EPP scenarios and Tessmann all have increasing performance with water month type, but MPOF is relatively flat and very low (about 10%) at LOI 2240, and decreasing across water month type at LOI 2090.

When looking across ecological scenarios, there is significant spread in performance values at LOI 2090 in all WMTs, whereas LOI 2240 has very little spread in CD months and much more in EW months. MPOF has the worst performance in EW months, while it is one of the best performing scenarios in CD months. EPP Max and Tessmann perform by far the worst in CD months at LOI 2090, while FFM and NCIFP join them at LOI 2240.

Frequency Reliability of Human Demands

At both locations, human frequency reliability is 0% in August regardless of human or ecological scenario (Figure 21a and c). Outside of the eWRIMS Storage Off scenario, there is very little variability in performance among human scenarios. In the eWRIMS Storage Off scenario, however, performance falls to zero from April to October at LOI 2090 and June to September at LOI 2240. Most of these months have better performance when eWRIMS Storage is used. Ecological scenario has a greater impact on human water supply performance, with MPOF resulting in 0% frequency reliability from June to September across scenarios and locations, and EPP 10 only having 0% in August and September and about 60% in January at both locations. However, the wet season performance is much higher in the eWRIMS Storage Off scenario in MPOF. Generally, the ecological scenarios that allow for the best human frequency reliability are EPP 10-75, POF 75%, and POF 80%. The variability in performance at either location by ecological scenario is most evident in the wet season, due to a decrease in performance to zero in August. Performance in July is very poor, with a max human frequency reliability of between 1% and 2.2%. Cannabis Demands 10x is much more important in July across all locations.

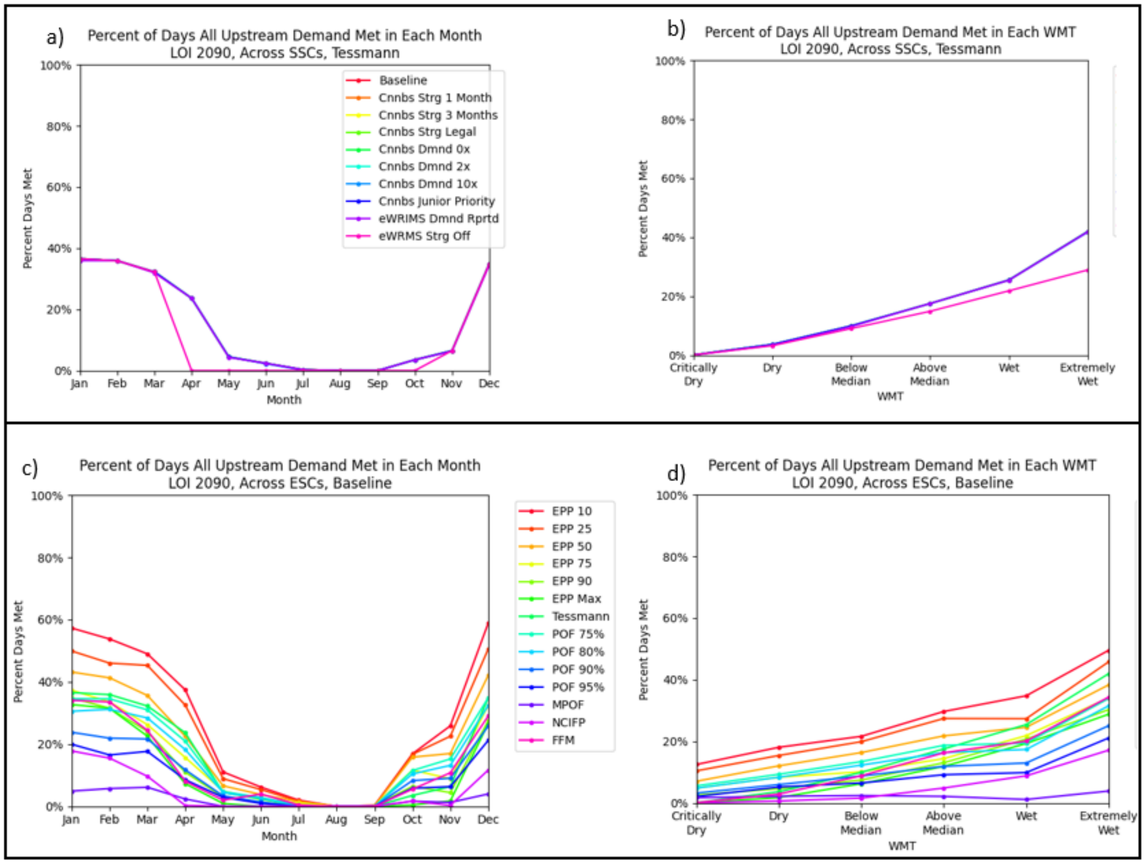


Figure 21 - Human frequency reliability at LOI 2090 by month and WMT in the Tessmann ecological scenario across human scenarios (a and b) and in the Baseline human sceanrio across ecological scenarios (c and d).

When looking across WMTs instead of months, eWRIMS Storage Off has a greater impact on performance than any other human scenario at LOI 2090 (Figure 21b and d). At LOI 2240 though, there is very little if any separation between human scenarios except in EW months when eWRIMS Storage Off has poorer performance than the others. All of the ecological scenarios, though, at both locations, perform better in wetter WMTs except MPOF which remains relatively constant. NCIFP, EPP Max, FFM, and Tessmann have the worst performance in CD months, neither of which have greater than 1% performance at either location. Though FFM and Tessmann have much worse performance in CD months relative to the other ecological scenarios, they are relatively better in EW months.

Mean Standardized Impairment (MSI)

MSI typically increases in drier months due to much lower flows. The largest MSI occurs in September in any scenario at LOI 2090 (Figure 22b and Figure 22d). Though MSI is much greater at LOI 2240, the largest MSI occurs in May here, which then decreases until August where there is 0% MSI (Figure 22a and Figure 22c). In the dry season, at both locations, the three positive cannabis scenarios have the least MSI. The Cannabis Junior Priority scenario is effective at keeping MSI low in the dry season at LOI 2240, though Cannabis Demands 0x and Cannabis Legal Storage are better, keeping MSI at about 0 from May to October regardless of ecological scenario. There is more variation between these scenarios at LOI 2090, with Cannabis Legal Storage being the best in summer months. There is little variation in MSI between ecological scenarios, though there is slightly more at LOI 2240. In the driest months, POF 75%-80%, EPP 10-50, and MPOF have the largest MSI, while NCIFP, and EPP 75-Max have the smallest MSI. MPOF has less MSI than other ecological scenarios at LOI 2240 as compared to LOI 2090. At LOI 2240, Cannabis Legal Storage has a greater MSI than Cannabis Demands 10x across all ecological scenarios in January. The decrease in MSI in Cannabis Demands 0x and Junior Priority in January is slight, but in July they make a much larger difference. Cannabis Legal Storage provides near zero MSI in July, with Cannabis Demands 0x and Junior as the next lowest.

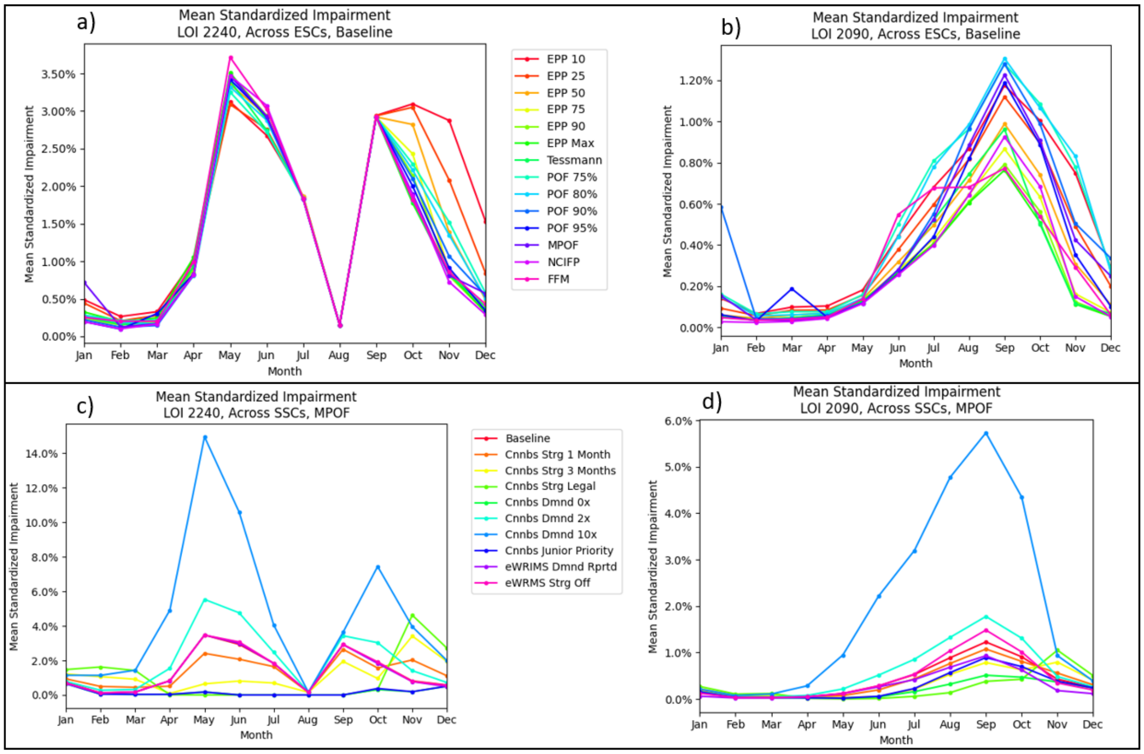


Figure 22 - MSI in each month at LOI 2240 and LOI 2090 in the Baseline human scenario across all ecological scenarios (a and b) and in MPOF ecological scenario across all human scenarios (c and d).

All ecological and human scenarios had greatest MSI in CD months and impairment decreased with increasingly wetter conditions, as would be expected. Cannabis Demands 10x always had the highest MSI while Cannabis Junior and Demands 0x typically had the lowest MSI. When looking across ecological scenarios, Cannabis Junior and Demands 0x had the widest variability in MSI in CD months due to EPP Max having near zero MSI in all WMTs, and POF 75%-80% having much greater CD MSI than EW MSI. Cannabis Legal Storage also has its greatest variability in CD months, though the lowest MSI ecological scenarios do not stay at 0% across WMTs like in the other two positive cannabis scenarios. The variability among ecological scenarios was similar at LOI 2240 and LOI 2090, only LOI 2240 had much higher values (Figure 23), and thus has a steeper decrease in MSI to EW months. MPOF saw an MSI near the median of the other ecological scenarios in CD months, and had the most MSI in EW months. Also, as

EPP increases, the MSI in the positive cannabis scenarios becomes less, especially in CD months and at all WMTs in EPP Max in the three positive cannabis scenarios.

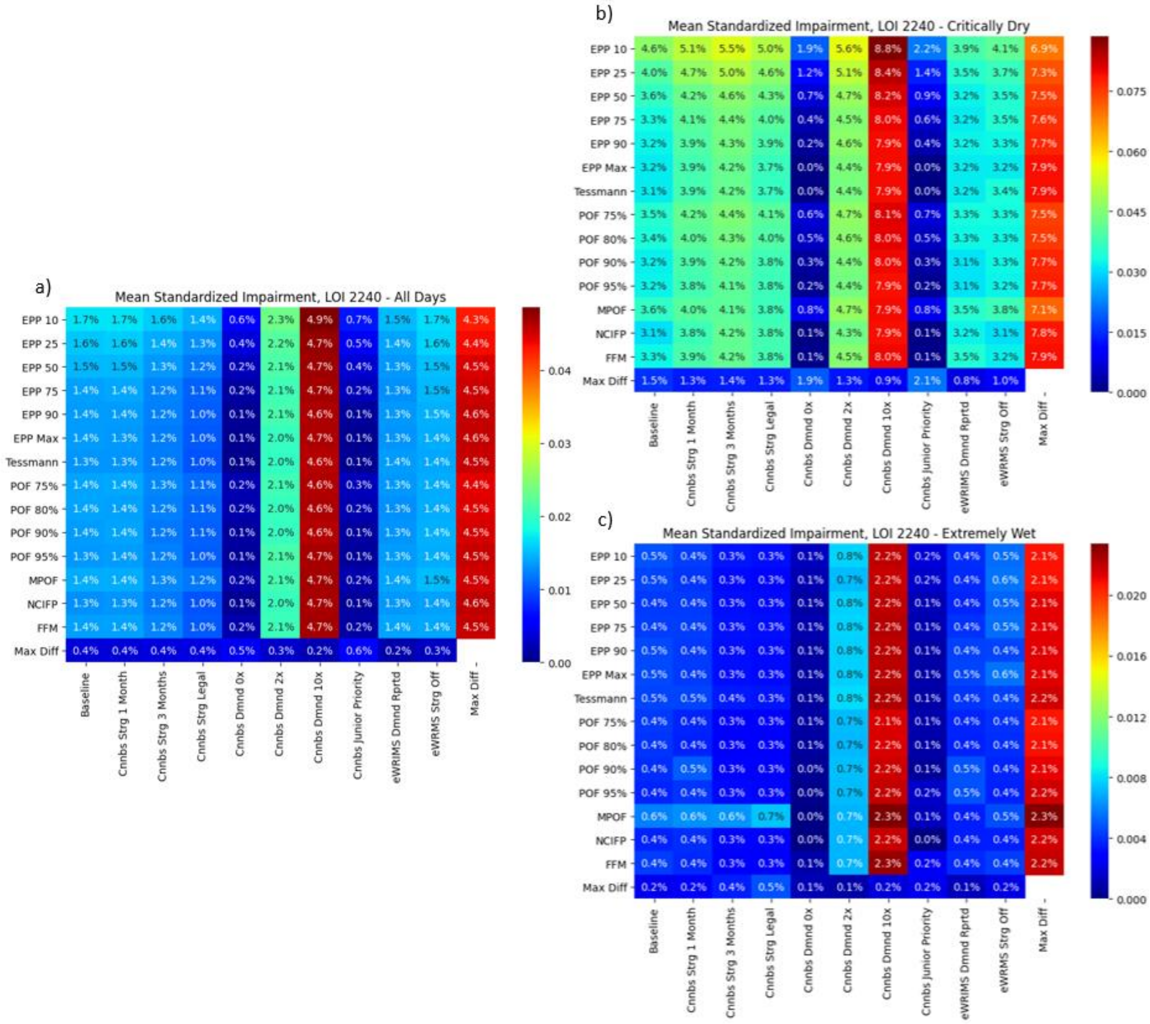


Figure 23 - Mean Standardized Impairment at LOI 2240 in every scenario combination in a) the POR, b) Critically Dry months, and c) Extremely Wet months. The 'Max Diff' row and column show the difference between the highest value and the lowest value of performance in each column and row

Question 4 – Climate & Management Relative Sensitivity

Frequency Reliability of Ecological Demands

Annual CMRS for ecological frequency reliability was typically higher across ecological scenarios than across human scenarios, being greater than 1 at larger CA locations. The climate variability was driven by the FFM scenario, which had lowest performance at the end of the dry season, and highest performance at the beginning of the dry season when the FFM IFT first transitions from its wet season value to the dry season value. The scenario variability is great across all months at larger CA locations. Smaller CA locations are water limited in the dry season as indicated by 0% performance in all ecological scenarios in August, which sets the lower bound on the climate variability. The upper climate variability limit in these locations is set by better performance in the wet season. The scenario variability is greatest in the wet season in these smaller CA locations, usually occurring between December and February. Specifically, Cannabis Demands 10x sometimes has higher CMRS due to worse performance across all months, which lowers the climate variability while keeping scenario variability similar to the value in other human scenarios. Cannabis Legal Storage often has a higher CMRS since it lowers performance in the wet season and raises it in the dry season, decreasing climate variability. Both of these are more impactful at smaller CA locations.

Conversely, when looking across human scenarios for each ecological scenario, most of the values of CMRS are below 1. This is because scenario variability is very low, with the only real separation in performance being the Cannabis Demands 10x scenario from the others. Annual climate variability is usually much greater than scenario variability with the wet seasons having high performance, and the dry season having very low performance – often with a limit set at 0 in August or September. CMRS is higher in NCIFP, MPOF, POF 90%, and POF 95% at larger locations since there is more separation between Cannabis Demands 10x and the other human scenarios, which increases scenario variability, and lower performance in the wet season, which decreases climate variability. EPP Max, FFM, and Tessmann often have low values of CMRS due to low scenario variability. LOI 2100 has greater values in most scenarios besides Tessmann and FFM than the other locations, with the POFs, MPOF, and NCIFP having values near or greater than 1. This is due to the three positive cannabis scenarios having a much greater impact in September with performance of 35-40% frequency and 0% in the others. Performance in these scenarios at LOI 2100 is also lower in the wet season, so climate variability is smaller than the scenario variability, which leads to a CMRS greater than 1.

Across WMTs, the largest scenario variability occurs in CD months at larger CA locations, but EW months at smaller CA locations. This is due to performance in CD months at smaller locations being very limited, with the highest ecological scenario achieving less than 20% frequency. Then, at these locations, scenarios like EPP 10 and POF 75% have increasing ecological frequency reliability by WMT while the worst-performing scenarios like MPOF stay relatively flat across WMTs, leading to the largest scenario variability occurring in the EW months. This is often demonstrated by a CMRS value of greater than 1 at these locations. At larger locations, however, performance is much more spread out between ecological scenarios in CD months, with harder scenarios like EPP Max and Tessmann having near zero performance and easier scenarios like EPP 10 and POF 75% having greater than 80% ecological frequency. As WMT increases, performance generally increases across ecological scenarios except MPOF which doesn't decrease enough to cause a larger scenario variability than in CD months. This is most evident in CMRS values just slightly less than 1.

The CMRS values across human scenarios for each ecological scenario for interannual variability are lower than 1 similar to those for annual variability. Most scenarios increase in performance with increasingly wet WMTs, especially Tessmann, EPP Max, and FFM. The scenario variability is usually small across human scenarios with Cannabis Demands 10x being the scenario that drives this variability, mostly doing so in CD months and at smaller CA locations. The POF 95% and NCIFP scenarios have low climate variability in all human scenarios, with significant scenario variability due to much more variability between Cannabis Demands 10x and the other human scenarios in CD months which leads to a higher interannual CMRS. Where available, these larger locations also have less climate variability in the lower EPP scenarios with increasing variability as EPP increases. The climate variability is similar at all EPPs in smaller locations.

Frequency Reliability of Human Demands

Annual CMRS across ecological scenarios for human frequency reliability is very similar between larger and smaller locations (Figure 24). This is because, at every location, climate variability is bound on the lower end by 0% performance in at least August and September. The upper bound of climate variability depends on the wet season performance in the best scenario, which is usually EPP 10 or POF 75%. Annual CMRS is slightly greater at LOI 2090 because scenario variability is lower. The three positive cannabis scenarios have a slight increase in annual CMRS from Baseline due to better dry season performance, which decreases the climate variability compared to other human scenarios. The eWRIMS Reported and eWRIMS Storage Off scenarios see decreases in annual CMRS. This is caused by an increase performance in the lowest scenarios (MPOF or NCIFP) in the wet season, where scenario variability is usually taken from, leading to a decrease in scenario variability.

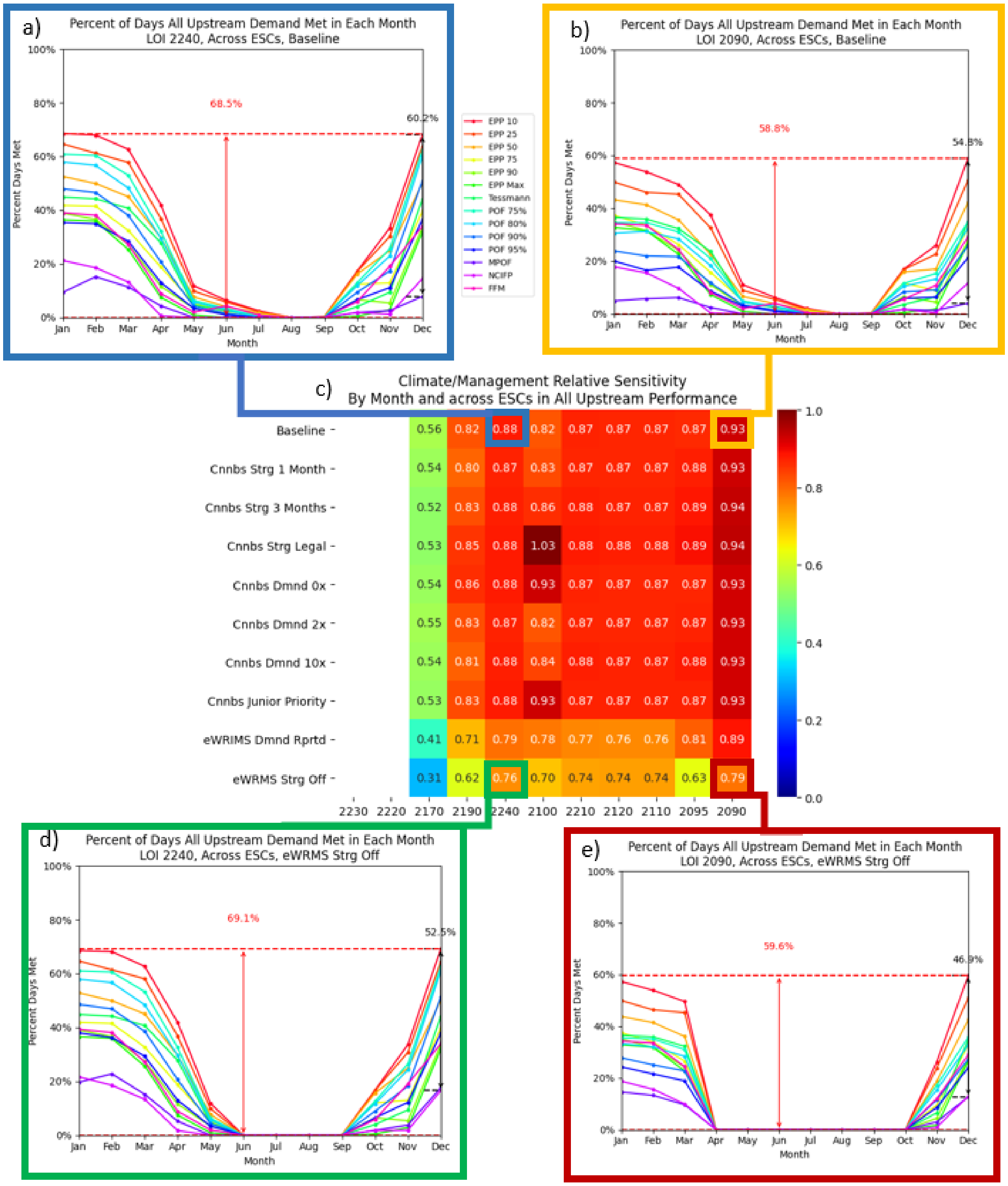


Figure 24 –Annual CMRS for human frequency reliability across all ecological scenarios by month for every human scenario and location (a). Human frequency reliability is shown across months with scenario and climate variability annotated for LOI 2240 and 2090 are shown for the Baseline (b and c) and eWRIMS Storage Off scenario (d and e).

The annual CMRS for human frequency reliability across human scenarios was much lower than across the ecological scenarios. The lower bound of climate variability is typically bound on the bottom by zero performance in the dry season, usually in the eWRIMS Storage Off scenario, with an upper bound of wet season performance. The largest values of scenario variability are often found in the beginning of the dry season, when eWRIMS Storage Off drops performance to zero, but other scenarios have non-zero performance. In MPOF, annual CMRS is generally higher than the others due to low wet season performance relative to other ecological scenarios and significant scenario variability in the wet season. This variability is between the eWRIMS Reported or eWRIMS Storage Off scenario on the high end and the positive cannabis scenarios on the lower end. Annual CMRS also decreases with increasing EPP due to decreasing scenario variability more than climate variability. NCIFP has consistently lower annual CMRS at most locations though it has similar climate variability to MPOF because the scenario variability is taken in October at much smaller values between eWRIMS Reported on the high end and eWRIMS Storage Off on the low end.

The different locations do not see significant variation in interannual CMRS across ecological scenarios, with CMRS usually near 1. The widest range of variability in interannual CMRS across ecological scenarios usually occurs in EW WMTs. The climate variability is usually taken from Tessmann or EPP Max which have the greatest increase in performance from CD to EW months. The scenario variability is usually taken in EW months, since MPOF has similar performance values across WMTs while others increase from CD to EW months. eWRIMS Reported has lower values of interannual CMRS because scenario variability is smaller due to MPOF, which is the lower bound of the scenario variability in EW months and has higher performance relative to its value in other human scenarios. eWRIMS Storage Off has much lower scenario variability in EW months due to better MPOF performance on the bottom end, and worse performance in other eco scenarios, which lowers interannual CMRS.

Interannual CMRS values across human scenarios are mostly less than one, similarly to annual CMRS. Again, this is driven by small separation between the human scenarios, and more significant climate variability. The exception is MPOF, which has similar performance values in the different WMTs, leading to a smaller climate variability value. MPOF also sees worse performance in eWRIMS Storage Off in EW months which increases scenario variability as well. There aren't significant differences between larger and smaller CA locations, though LOI 2240 stands out because there is very little scenario variability due to almost no separation between the bulk of the human scenarios and eWRIMS Storage Off – even in EW months. As POFs and EPPs increase, the human scenarios with the highest performance decrease, such that there is less scenario variability and, thus, lower interannual CMRS. NCIFP is also consistently small, specifically in larger LOIs, due to very small scenario variability.

Mean Standardized Impairment (MSI)

As discussed in previous questions, MSI is most influenced by scenarios that involve alterations to unpermitted cannabis demands or storage. Specifically, the Cannabis Demands 0x and Cannabis Junior Priority scenario have annual CMRS values of approximately one at all locations. This is because scenario variability is roughly equal to the climate variability, with less difficult ecological scenarios that usually have zero or near-zero MSI in wetter months and high MSI in dry months, and more difficult ecological scenarios having near-zero MSI in those drier months. Conversely, Cannabis Demands 10x has a very low annual CMRS across all locations because climate variability is much larger compared to other human scenarios. This is driven by the dry season seeing the highest values of MSI of any human scenario in Cannabis Demands 10x. Also, as more cannabis storage is implemented, annual CMRS decreases. This is due to a near-zero MSI in the dry season that increases in the wet season as more cannabis storage is implemented. This leads to a larger climate variability than scenario variability.

The annual CMRS is always much greater than one when looking across human scenarios instead of ecological scenarios (Figure 25). This is driven by Cannabis Demands 10x having the highest MSI by far of any human scenario, especially in the dry months and at smaller locations, with other scenarios like Cannabis Legal Storage having very low, if not zero, MSI in dry months. This leads to the scenario variability always being much larger than the climate variability. The variability in annual CMRS between all of the ecological scenarios is smaller at smaller CA locations since there is less water available. At larger locations, CMRS increases as EPP increases, while annual CMRS decreases with increasing EPP at smaller CA locations. This is because increasing EPPs at larger locations cause decreasing values of climate variability without affecting scenario variability much if at all since Cannabis Demands 10x affects MSI similarly across ecological scenarios. At smaller locations, however, scenario variability increases, causing a slight drop in annual CMRS. In general, MPOF has a lower value of annual CMRS due to greater MSI in September which increases climate variability.

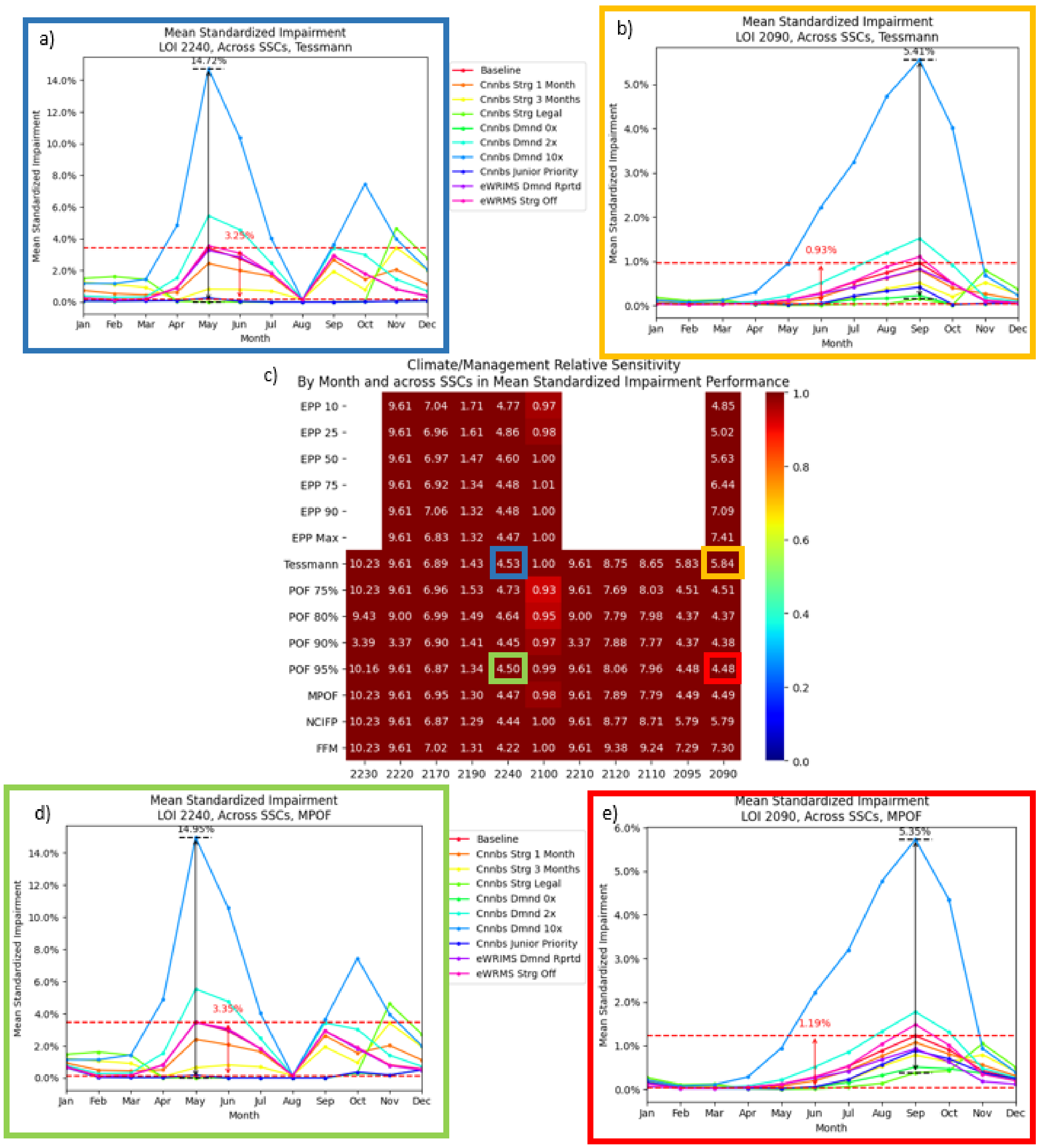


Figure 25 - Annual CMRS for MSI across all human scenarios by month for every ecological scenario and location (c). MSI is shown across months with scenario and climate variability annotated for LOI 2240 and 2090 in Tessmann (a and b) and MPOF scenario (d and e).

Interannual CMRS for MSI across ecological scenarios has similar trends to annual CMRS (Figure 26). Cannabis Demands 0x and Cannabis Junior Priority have consistently the highest values of interannual CMRS, usually being slightly greater than one. These scenarios have greatest scenario variability in CD months, being bound on the lower end by near-zero MSI in the more difficult ecological scenario like EPP Max and on the higher end by EPP 10 or POF 75%. The climate variability in these usually is similar to scenario variability since MSI decreases from CD to EW months, with near zero EW MSI. The scenario variability. In other human scenarios, the scenario variability does not have a lower bound of zero MSI like in these, which makes scenario and climate variability differ more. Interannual CMRS is usually lowest in the Cannabis Demands 10x scenario due to ecological scenarios having high MSI in CD months with little scenario variation, while MSI is significantly lower in EW months. Smaller locations have lower values of interannual CMRS than larger locations due to higher values in general of MSI in each WMT.

Interannual CMRS across human scenarios are all greater than one. Again, this is driven by Cannabis Demands 10x creating large separation from the other human scenarios, which leads to greater scenario variability across all locations and ecological scenarios. Larger locations have higher interannual CMRS due to the baseline scenario having very little climate variability across WMTs. Also, as ecological scenarios become more difficult (e.g., increasing EPPs or POFs), the value of interannual CMRS increases due to a decreasing climate variability from lower in MSI in CD months and the same MSI in EW months. Tessmann has consistently higher values of interannual CMRS, especially at larger locations, than other ecological scenarios due to lower MSI in CD months and higher MSI in EW months in the baseline scenario, which decreases climate variability.

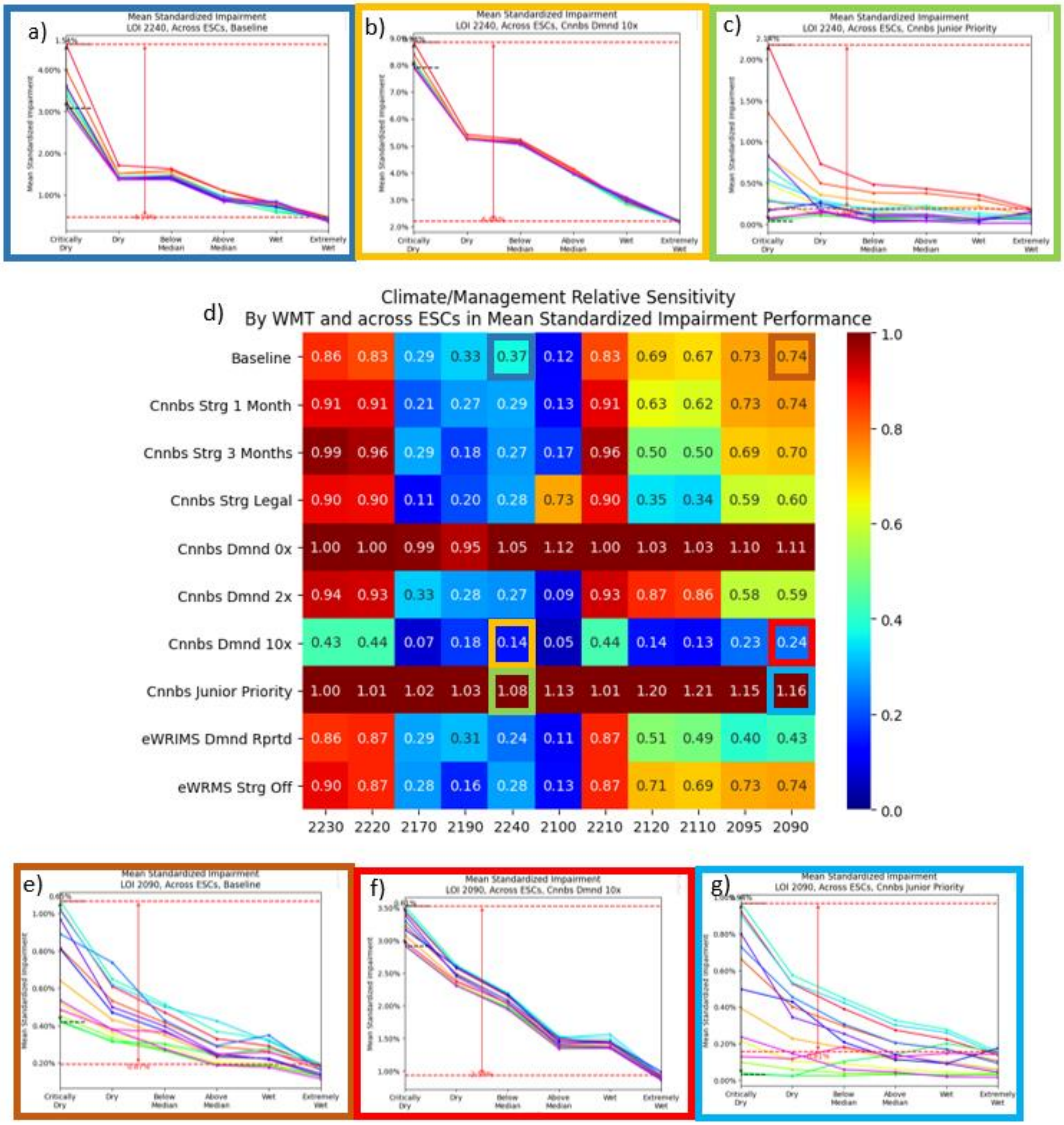


Figure 26 - Interannual CMRS for MSI across ecological scenarios for each human scenario and location (a). MSI is shown across WMTs with climate and scenario variability annotated for the Baseline, Cannabis Demands 10x, and Cannabis Junior Priority scenarios for LOI 2240 (b, c, and d) and LOI 2090 (e, f, and g)

DISCUSSION

This thesis study addresses and evaluates the ability of a highly seasonal, unregulated watershed with distributed diversions and varying amounts of off-stream storage to provide water to numerous demands. A DSS framework and analysis tools were developed to convey this information to watershed stakeholders. The SFER was selected for its high seasonal and inter-annual hydrologic variability as well as substantial distributed permitted and unpermitted water demands that are asynchronous with natural water availability and increase stress on highly threatened and endangered native aquatic species. The DSS presented here allows water managers to address several sources of uncertainty in both current and future human and ecosystem water demands and hydrologic conditions. It also provides clear and versatile visualizations and analyses of water allocation model results through a web-based user interface tool that is publicly available for any interested groups such as water managers, watershed stakeholders, researchers, and other organizations that could benefit from this information. Additional analyses performed as part of Objective 3 address key research questions and complement the results provided in the user-interface, providing information on how watershed characteristics effect human and ecological water resources performance to support prioritization of management actions, with potential to inform management decisions in other similar watersheds.

The DSS addresses several major sources of uncertainty in this type of system related to current and future human and ecological water demands. Current and future uncertainty in the amount and timing of human water demands was addressed through development of several hypothetical scenarios. Specifically, uncertainty in unpermitted demands was considered by adjusting the amount of unpermitted demands in the Cannabis Demands 0x, Cannabis Demands 2x, and Cannabis Demands 10x scenarios, and in permitted demands based on actual reported diversion rates rather than what is permitted in the eWRIMS Reported scenario. The storage-based scenarios were implemented to consider uncertainty in the amount and timing of off-stream storage used to supply unpermitted water demands using the Cannabis 1-Month Storage, Cannabis 3-Month Storage, and Cannabis Legal Storage scenarios (Figure 22, Table 3). These scenarios all address current uncertainty in estimations of water demands storage that are a result of the hidden nature of the operations, forest cover, and recent policy changes (Dillis et al. 2019, SWRCB 2019), and future uncertainty based on how these demands and the amount of storage may change given uncertain future conditions, including those as a result of climate non-stationarity. The DSS also accounts for the uncertainty in the approach used to develop IFTs by considering 15 different IFTs based on 6 different top-down and bottom-up approaches.

In general, DSS results demonstrated that unpermitted demands have a large impact on water availability in the already critical dry season due to their removal of water from the stream, while off-stream storage tanks provide the ability to overcome some of this seasonality by shifting diversions to the wet season (Figure 22). When unpermitted cannabis demands were increased, the ecological frequency reliability and MSI were impacted the most, while removing cannabis demands and setting their priority below that of the IFT was much more successful at removing the stress put on the system by these demands (Figure 19, Figure 22). Providing legal amounts of storage to unpermitted cannabis demands further improved performance in the dry season, but at the expense of wet season performance, indicating additional storage capacity may be needed in the watershed for these users. Similarly, storage for permitted human demands was found to be most important in meeting human demands in the dry season, even demonstrating that this storage is the sole provider of water to permitted human demands in the dry season across the watershed (Figure 21).

Varying the amount and storage for human water demands and particularly unpermitted demands has a greater effect on ecological performance than the implementation of different IFTs (Figure 15, Figure 19, Figure 22), while the selection of IFT has a greater effect on human demand performance than changes in human demand patterns (Figure 16, Figure 21). This initially seems counterintuitive – but is simply a result of the modeled policy structure. By definition, human water demands remove water from the stream, which leaves less water in-stream to meet IFTs. Therefore, greater demands results in less water in-stream. On the other hand, IFTs are set to represent in-stream ecosystem water needs at varying levels. And, since permitted human demands are only allowed to divert when flows exceed IFTs during certain non-forbearance periods, setting higher IFTs leaves less water available to be diverted. This is evidenced by the values of CMRS, which are much higher for MSI across human scenarios (Figure 25) indicating that they have a larger impact on the amount of water instream than the natural climate variability, while CMRS in human frequency reliability is much higher when looking across ecological scenarios (Figure 24).

While setting IFTs to lower flow or less ecologically conservative values provides more ability to meet human demands (Figure 21), there is less water remaining instream due to more diversions occurring (Figure 22) which may be detrimental to the aquatic ecosystem (Merenlender et al. 2008). MPOF has demonstrated its versatility by providing a higher both annual and interannual CMRS value in both frequency of ecological and human demands, indicating that it provides more ability to overcome climate variability. Though this could just be due to low performance across the year for annual CMRS, MPOF's low interannual CMRS is a result of performing better relative to other ecological scenarios in CD months. Based on this, setting IFTs using static diversion limits as opposed to calculations of instream flow may be more equipped to handle interannual seasonality. This is further evidenced by the large climate variability in Tessmann across WMTs, which is set based on static flow targets from year to year. MPOF has the potential to be very useful if the diversion limit calculations are adjusted to provide better all-around performance. Similarly, Tessmann may also be adjusted to consider more interannual variability in its calculation.

Setting unpermitted cannabis demands to a lower priority than the IFT had a very similar level of impact to removing unpermitted cannabis demands entirely (Figure 15, Figure 22). Doing this is analogous to bringing users with unpermitted diversions for cannabis cultivation into compliance with state legislation since permitted demands have a lower priority than IFTs. This finding supports the ongoing effort by water managers to bring unpermitted users into compliance so that they can be better managed in the context of hydrologic variability and high water demands.

Additional analysis of brining unpermitted water users into compliance is needed since our results only focus on performance of currently permitted demands. If these unpermitted users were brought into compliance, performance of these newly permitted demands would need to be calculated alongside already permitted demands to determine how all diverters are impacted and how often new water permit holders could meet their allocations. Higher values of CMRS in Cannabis Demands 0x and Cannabis Junior Priority and lower values of CMRS in Cannabis Demands 10x in MSI further strengthen the argument to regulate these unpermitted cannabis demands since it provides water managers with more ability to overcome climate variability by setting IFTs appropriately (Figure 25, Figure 26). The Cannabis Junior Priority scenario assumes that 100% of unpermitted diversions are brought into compliance. In reality, this would be expensive, time-consuming, and difficult to accomplish since many of these operations intentionally choose hidden locations to avoid unwanted detection and costs (Dillis et al. 2019).

The lower flows in small headwater sub-catchments were found to be a major influence on performance, especially in the dry season. This is evidenced by increased unpermitted demands being more important at smaller CA locations, lower values in general of CMRS at LOI 2240 than LOI 2090 (i.e., more at the mercy of the climate here), and larger CA locations having large climate variability in CD months while the climate variability in smaller CA locations is much more limited (Figure 22, Figure 25, Figure 26). Small headwater sub-catchments are critical for aquatic ecosystems seeking cold water refuge in the summer months and should be monitored closely since water management decisions do not appear to provide the ability to overcome this lack of water instream. Water managers could, however, expand or encourage the use of off-stream storage to reduce water deficits to irrigators in the dry season to some extent. These locations should also be watched closely due to the prevalence of cannabis water uses in these densely forested headwater locations (Butsic and Brenner, 2016).

This research study and DSS framework are powerful in their ability to provide insight into many different dimensions of water management over an entire watershed, including the relative impact of unpermitted and permitted demands, storage for these demands, ecological water needs, and how these vary with hydrologic variability and spatial heterogeneity of watershed characteristics (Table 3, Table 4, Table 5, Table 8, Figure 14, Figure 18). The DSS framework allows each of these factors to be isolated and analyzed both individually and in combination with other factors through space and time. The DSS allowed for the quantitative analysis of the impacts of different management decisions on the delivery of water to different demands (Figure 6, Figure 9, Figure 12). In addition, it provides a fully automated way to calculate the different IFTs given input hydrology or historic flow data. Many of these IFT determination methodologies have current or future management implications, whether they were used to determine environmental flows previously (e.g., Tessmann), or there is specific interest in using them in the future (e.g., MPOF). The development of the eWRIMS Analyzer allows for the automated extraction and analysis of eWRIMS demands in any watershed in which eWRIMS is used. Finally, the GUI allows DSS results to be presented clearly and concisely, and for stakeholders to obtain detailed information about specific locations, seasons, or scenarios of interest.

The collaborative nature of the DSS development process is a major strength of this research. Structured stakeholder interactions provided the ability to include the perspectives of many watershed stakeholders, including those who have interest in the ecosystems supported, human water demands, or both. They also provided the ability to improve understanding of uncertainty in the system. However, the process of involving numerous stakeholders did have some challenges. The largest of these involved difficulty in coming to agreements on DSS structure and key components among the many stakeholders. While this was mostly manifested in the form of longer model development time than initially anticipated, it forced DSS developers to focus on appropriately expressing fundamental structure and concepts including variability and uncertainty so that the complex water system could be accurately represented. Deciding how to represent uncertainty was also a challenging task due to the quantitative nature of the data, tools, and visualizations in order to appropriately inform water management decisions.

Identified water resources performance trends with respect to RSPs indicate some potential to predict human and ecological performance at locations that have not been modeled in the DSS or in other watersheds based on their RSP values. Since developing predictive machine learning models was not the goal of this research study, there would likely be significant noise in predicting performance from RSPs at other locations due to so few data points and lack of robust statistical modelling to determine the appropriate relationships. However, the observed trends in performance (Figure 13, Figure 14, Figure 18) are strong enough to indicate their utility for such a modeling exercise, which would greatly reduce the data and computational resource requirements of this effort as an initial screening tool for other locations or watersheds. In order to determine the scalability of using RSPs to predict performance, further research is recommended to determine how many locations and over what range of watershed characteristics are needed to predict performance outcomes or highlight bright spots or hotspots (Figure 11), and how robust these relationships are across watersheds. It is also recommended to extend this effort to determine which RSPs have the most control on these relationships in other watersheds and how easily they can be estimated across a watershed. For example, relationships driven by hydrology or geomorphology/geology variables would be easier to estimate with available data than demand-based RSPs, that would require estimates of permitted and unpermitted water demands to determine RSPs at new locations. Regardless, this exercise would help researchers prioritize data collection efforts in the SFER and other study watersheds.

The CMRS summary performance metric introduced in this thesis was able to quantitatively distinguish the relative roles of climate and scenario variability on performance outcomes. CMRS results indicated how much, if at all, management decisions may be able to make up for the impact of natural seasonal and interannual climate variability (Figure 24, Figure

25, Figure 26). Considered over a large set of locations, it is possible that CRMS thresholds could be identified to highlight locations that require special attention due to being much more heavily influenced by climate than management decisions. These thresholds may depend on watershed (e.g., seasonality or availability of instream or off-stream storage) or management priorities (e.g., IFT or human water demands priority). In summary, CMRS has broader potential for water managers to quickly identify locations of interest and the relative power of their decisions. It may also be useful as another way of describing how difficult meeting water demands will become in an uncertain climate future. Specifically, CMRS values could be compared between water allocation model results under current hydrologic conditions

As a new metric, CMRS should be used with caution since it is highly dependent on how scenarios are defined. For example, if SEWAM had a Cannabis Demands 1000x scenario, CMRS across human scenarios would always be very high due to extremely high scenario variability. It is also difficult to distinguish changing CMRS value by whether scenario variability or climate variability is changing. This is an important distinction because higher scenario variability indicates that a management or scenario change can be made to overcome climate variability, while climate variability may not. Additional sensitivity analysis of the CMRS metric across scenarios could improve understanding of when and how to best apply and interpret this metric.

While the DSS is capable of analyzing water allocations to the different demands across many different dimensions, there are still several limitations of this framework and study, including data and computational requirements, challenges of accounting for uncertainty, and limited sample size. First, the DSS required a large amount of data and understanding of the watershed current and proposed management policies. Data requirements included unimpaired hydrology data, either from a hydrologic model or field observations, estimates of permitted and unpermitted water demands, and flow-ecology relationships or biological monitoring data to evaluate ecological performance of the different scenarios. Additionally, there are significant computational resources required to limit SEWAM run time. Even though cloud computing was used to run each of the 150 scenario combinations in parallel at each location, the model still takes approximately one week to complete. While water demands could be estimated in our study watershed using the eWRIMS database and analyzer tool, it is only applicable in regions where such electronic water rights databases are available.

Next, while the DSS addresses some types of uncertainty, there is additional uncertainty sources outside of the scenarios proposed here that were not considered. For example, we employed 15 different ecological scenarios containing different IFTs, but only one kind of bottom-up method that considers only one life stage of one species. There may be others that represent the water needs of other important native species or some other essential ecosystem process. Similarly, this DSS currently only evaluates ecosystem performance based on the ability to provide IFTs. The DSS currently lacks the ability to link these ambient instream flows to other ecosystem health metrics, for example, by determining FFMs (Yarnell et al. 2019) or using available flow-ecology relationships that more directly related instream flow to ecological outcomes (e.g., Richter et al. 2006, 2011, Poff et al. 2010). This functionality will be added to the DSS in the future. Finally, limited sample size at this point in the modeling effort precluded quantitative assessment of statistical significance of different trends and scenarios.

Several opportunities exist to improve the DSS in future work, including revision and addition of scenarios and more robust statistical analyses of model results for larger study areas with more sub-catchments. First, given that the final version of SEWAM will include 392 locations, statistical tests like Kruskal-Wallis/Dunn's test (Kruskal &Wallis 1952, Dunn 1964) or machine learning techniques for feature selection (e.g. Random Forest Models [Breiman 2001]) could be used to assess performance differences between scenarios or RSPs. Additional model fitting analysis could improve the choice of model used to describe the relationship between performance metrics and RSPs (e.g., higher order polynomial, logarithmic). Similarly, CMRS should be further be analyzed by determining the appropriate relationship between RSP and CMRS, like what was done in research question 2b. Also, SWRCB has indicated that there may be additional unpermitted demands that represent illegal domestic uses on top of the unpermitted cannabis demands. These are planned to be added to the DSS in future model iterations. The impact of these demands should be analyzed, with potential new scenarios to determine model the uncertainty in these similar to the uncertainty analysis of the cannabis demands. It would also be advantageous to have the ability to turn on and off groundwater pumping such that the impacts of this can be analyzed as well. Also, evaluating SI by the maximum value that occurs as well as the mean value that occurs is of particular interest, since these maximum impairment events may lead to critical habitat conditions with severe impacts for aquatic species population dynamics. For example, if impairment is so great that the habitat becomes disconnected, this could completely obstruct to fish passage. This was considered early in the analysis, however an error in WEAP did not allow for appropriate values of maximum SI to be calculated. Finally, future analyses should also be performed on other watersheds to determine which, if any, of these analyses are independent or dependent on watershed characteristics.

CONCLUSIONS

This thesis presents a DSS that is capable of analyzing water allocation trends in a highly seasonal watershed in northern CA with significant human demands of both the permitted and unpermitted variety, which hosts threatened and endangered native aquatic species and has no significant instream storage infrastructure. In particular, this research demonstrates to water managers where meeting water demands is the most difficult. Unpermitted cannabis demands were found to have significant impacts on the ability to meet water demands, especially in the dry season. Meeting water demands was also much more difficult at headwater locations, where less water is available and unpermitted diverters are concentrated so their operations can be hidden by the dense forestry. The inability of the system to meet water demands in the dry season can be mostly overcome by the implementation and expansion of off-stream storage for these unpermitted demands. The importance of off-stream storage is also evident in the ability of the system to provide water to the permitted human demands, demonstrating that often in the dry season, permitted human demands are only provided for from off-stream storage. The impact of permitted demands on instream flow can be managed by setting higher IFTs, though this will come at the cost of being able to meet the human demands.

The DSS also includes many publicly-available tools. The most important of these tools provides the ability to portray performance from many different perspectives through the development of a publicly available user-interface. These different perspectives are addressed through the use of temporal dashboards, which include time series of multiple performance metrics, spatial dashboards with the ability to identify ‘bright spots’ and ‘hot spots’ and show performance at any location throughout the watershed, and tradeoff dashboards that show performance difference between scenarios. The DSS also includes the ability to programmatically calculate IFTs using the python module developed and programmatically extract eWRIMS demands using the eWRIMS Analyzer.

The largest limitation in the current state of this DSS and research is only having 11 locations of data. This inhibits the ability to obtain meaningful statistical relationships that can be used to predict performance in other locations or other watersheds. However, as noted, there is an excessive amount of data due to 150 scenario combinations of 21 years of daily time series. So, when expanded to all locations in the SFER, significant data processing and computation time will be needed such that different techniques may be needed. This research also introduces the CMRS variable which is powerful in determining if performance at a given location is mostly controlled by the natural hydrologic variability, or if this variability can be overcome with different management decisions. CMRS, as well as the RSP analyses, may allow water managers to quickly identify locations that should be focused on without the need of running a water allocation model to determine performance.

DATA AVAILABILITY

A publicly available version of the code and data used to perform the analyses presented in this research are available on github at https://github.com/jesserowles/Public_JLR_Research_SFE. This repository includes flow data that is arbitrary and is not associated with any location used in this research.

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APPENDICES

Appendix A - Additional Details of IFT calculation

Ecological Performance Percentiles and Area Weighted Suitability

The EPP approach uses Area Weighted Suitability (AWS), which is a unitless metric that evaluates the suitability of hydraulic habitat at a given location, to determine IFTs. It was calculated by dividing each individual reach at a given discharge into cells where each cell contains a depth and velocity. The cell depths and velocities are associated with a habitat suitability based on pre-determined suitability curves at different flows. The suitability associated with each cell was then summed over each cross section. The number of occurrences of each cross-section’s suitability was calculated over the reach of interest which was multiplied by that suitability to obtain a weighted suitability for each cross section. AWS is the sum of each cross section’s weighted suitability. Because suitability curves vary based on species life stage, obtaining a complete picture of how suitable a flow regime is over the entire life cycle of a species would require AWS calculations to be performed for every life stage of that species. In this case study, suitable habitat conditions were determined for the juvenile life stage of steelhead salmon by CDFW at a range of discharges. This AWS-discharge relationship is henceforth referred to as an Ecological Performance Function (EPF) and was used to obtain AWS as the instream flow metric used to evaluate flow-specific ecosystem performance (Figure 27).

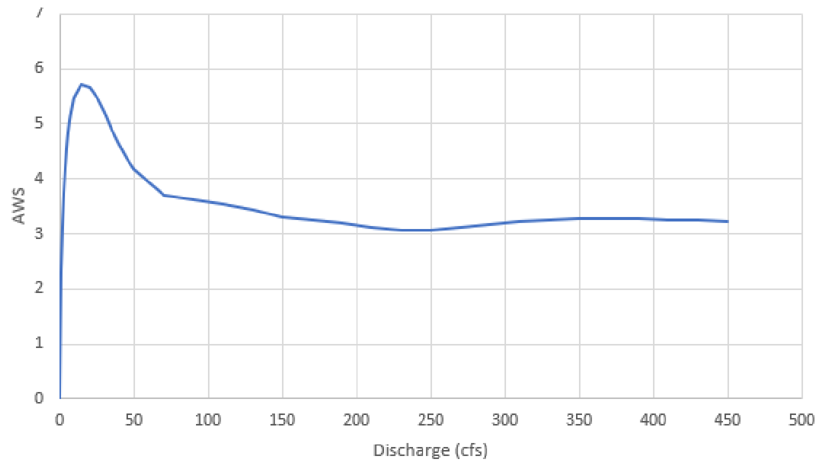

Figure 27 - Example of an Ecological Performance Function (EPF) which provides some measure of ecosystem health or habitat suitability as a function of discharge at a specific location. This example uses Area-Weighted Suitability (AWS) as the ecosystem health metric.

EPFs were used at five out of the available 11 locations to determine IFTs at different percentiles. Unimpaired hydrology data was used to determine the Water Month Type (WMT) of each month in the period of record. Water month type was calculated from mean monthly flow based on modeled unimpaired daily stream-flow over water years 1995-2019. Critically dry months are exceeded by >90% of the mean monthly flows, dry months are exceeded by 70-90%, below median months are exceeded by 50-70%, above median are exceeded by 30-50%, wet months are exceeded by 10-30%, and extremely wet months are exceeded by <10%. The unimpaired hydrology data was classified into six water month types – Critically Dry (CD), Dry (D), Below Median (BM), Above Median (AM), Wet (W), and Extremely Wet (EW). Once the flow data was separated into the WMTs, the daily flows in each WMT can be used to determine corresponding AWS values given the EPF for that location. Then, percentiles of this set of AWS values were taken for each water month type and each calendar month. These were then converted back to flow so that different percentiles could be translated into IFTs. Since the EPFs typically have a peak AWS value somewhere in the middle of the EPF (i.e., not on either the high-flow or low-flow end), IFTs were not provided at values higher than the peak AWS flow.

North Coast Instream Flow Policy (NCIFP)

The details of how NCIFP IFTs are calculated as outlined above. To improve understanding of this method, a detailed example is outlined here. Using the outlet of Redwood Creek which has a mean annual flow of 75.55 cfs, a drainage area of 26.05 mi^2, and a bankfull flow of 1862.41 cfs, the Q_{MBF} can be calculated as 143.65 cfs and the Q_{MCD} as 93.12 cfs (Table 12). This means that when stream-flow exceeds 143.65 cfs, diversions cannot exceed 93.12 cfs in total and can only achieve that diversion rate if the total amount of instream flows exceed $Q_{MBF} + Q_{MCD}$=143.65 cfs + 93.12 cfs = 236.77 cfs. If unimpaired flows are between 143.65 cfs and 236.77 cfs, only the amount above 143.65 cfs can be diverted. Ultimately, the diversion rate will be between zero and Q_{MCD} at a given location. This example is shown in for clarity.

Table 12 – Example North Coast Instream Flow Policy diversion allocation calculation for Water Year 2014 at Outlet of Redwood Creek.

<table>
<tr><th colspan="4">Diversion Allocation Determination for Water Year 2014
At Outlet of Redwood Creek, Q_{MBF} = 143.65 cfs, Q_{MCD} = 93.12 cfs</th><th></th></tr>
<tr><th></th><th>Date</th><th>Stream-flow (cfs)</th><th>Diversion Allocation (cfs)</th><th></th></tr>
<tr><td rowspan="4">Did not exceed Q_{MBF}</td><td>**24-Mar**</td><td>68.11</td><td>0</td><td rowspan="8">Within season of allowed diversions</td></tr>
<tr><td>**25-Mar**</td><td>68.40</td><td>0</td></tr>
<tr><td>**26-Mar**</td><td>76.83</td><td>0</td></tr>
<tr><td>**27-Mar**</td><td>79.70</td><td>0</td></tr>
<tr><td rowspan="4">Exceeded Q_{MBF} and within diversion season</td><td>**28-Mar**</td><td>497.91</td><td>93.12</td></tr>
<tr><td>**29-Mar**</td><td>282.73</td><td>93.12</td></tr>
<tr><td>**30-Mar**</td><td>203.75</td><td>60.10*</td></tr>
<tr><td>**31-Mar**</td><td>257.71</td><td>93.12</td></tr>
<tr><td rowspan="3">Exceeded Q_{MBF} but outside diversion season</td><td>**1-Apr**</td><td>236.23</td><td>0</td><td rowspan="3">Outside season of allowed diversions</td></tr>
<tr><td>**2-Apr**</td><td>197.18</td><td>0</td></tr>
<tr><td>**3-Apr**</td><td>169.53</td><td>0</td></tr>
<tr><td colspan="4">* Note that this value is less than $Q_{MCD} = 93.12\ cfs$ since the stream-flow is less than $Q_{MCD} + Q_{MBF} = 236.77\ cfs$.</td><td></td></tr>
</table>

Estimating IFTs using the NCIFP method relied on the assumption that Q_{MCD} represent all upstream demands. This means, for example, that if Q_{MCD} is calculated to be 10 cfs at a location of interest, but 2 cfs of diversions occur upstream, only 8 cfs can be diverted. Since

SEWAM is not configured to consider upstream demands when determining diversion allocations at the current location at this time, the assumption is that the Q_{MCD} calculated applies at the location of interest. This is somewhat accounted for by subtracting diversion allocations from the unimpaired flow to obtain IFTs. This means that, for example, at some upstream location, the unimpaired flow is 20 cfs, and 2 cfs are diverted, 18 cfs remain instream. At a location just downstream, if the unimpaired flow is also 20 cfs, and the Q_{MCD} is calculated as 4 cfs, the IFT will be set as 20 – 4 = 16 cfs. Since 18 cfs is actually what is available after upstream diversions, the amount that can be diverted at the downstream location will be only 2 cfs since 18 cfs (incoming flow) – 16 cfs (IFT) = 2 cfs. Based on this, the NCIFP IFTs should provide approximately the correct diversion allocations as implemented by the actual policy.

Appendix B - Statistical Analyses

To analyze performance trends between RSPs and the different performance metrics in the complete version of SEWAM, an R toolbox that was developed to determine relationships between predictors and resulting variables was used. This toolbox leverages functions from the 'mlr' toolbox in R, which provides machine learning toolboxes to the R programming language including mutual information gain, ANOVA, random forest model importance, and linear correlation coefficients. R code was developed to be able to run this functionality on SEWAM results to determine what metrics of performance have the most statistically significant relationships with which RSPs. Then, once the metrics of performance that have the strongest relationships with RSPs are selected, these metrics of performance can be compared back again to each RSP to determine which RSPs have the strongest correlation with the different metrics of performance.

This is the most statistically robust way to perform this analysis. However, because there are only 11 locations that have results in the current version of the model, there are limitations in the results of this analysis due to the small sample size which have an impact on any statistical analyses performed on these. This is most evident when the mlr toolbox is used, and, under any statistical test provided, most of the metrics of performance come back with the same value of correlation as each other. This means it is impossible to distinguish which metrics of performance are the most statistically significant since there are many metrics with the same value of statistical significance (Figure 28).

Figure 28 - Results of the feature_importance R function on UDPS using the 'FSelectorRcpp_information.gain' function, which is aimed at obtaining which predictors provide the most information gain. As can be seen, all 50 variables shown have the same result of the statistical test.