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Accounting for Critical Attributes and Uncertainty in Flow-Ecology Relationships

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ACCOUNTING FOR CRITICAL ATTRIBUTES AND UNCERTAINTY IN FLOW-ECOLOGY RELATIONSHIPS

by

Elizabeth Decker Morgan

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ABSTRACT

Accounting for Critical Attributes and Uncertainty in Flow-Ecology Relationships

by

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Utah State University, 2021

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Department: Civil and Environmental Engineering

Environmental flows are increasingly used to maintain desired ecological outcomes for rivers while also sustaining human water requirements. While there are numerous approaches to develop environmental flows, they all rely on a strong conceptual understanding of how streamflow affects aquatic and riparian species, either directly or indirectly through mediating factors such as physical habitat conditions. However, our understanding of flow-ecology relationships is often limited and uncertain. Uncertainty in flow-ecology relationships can stem from using limited data to develop or test relationships or an incomplete understanding of the attributes inherent to each relationship, such as the channel morphology setting, climate, or other critical controls. Further, even if there is certainty for location- and species-specific relationships, there is often uncertainty in how these relationships scale across space and time or how they may change under future climate conditions.

Accounting for attributes and uncertainty in flow-ecology relationships is critical to develop and implement environmental flows at watershed or larger scales with limited information and to address widespread degradation of river ecosystems. Using the South Fork Eel River watershed in northern California USA as a case study, I explored attributes and uncertainty in flow-ecology relationships through a systematic review of peer-reviewed studies and Bayesian Network modeling and scenario analysis. Most studies in the watershed encompass species – species relationships (e.g., predation) or physical condition – species relationships (e.g., water temperature – species growth), but few studies provide explicit links between the flow regime and ecological outcomes. Further, disconnects in the temporal and spatial extent and resolution of existing studies and in the species studied increase challenges for understanding and applying flow-ecology relationships at the watershed scale. These uncertainties informed several scenarios—represented as different probability sets—in an exploratory Bayesian Network model for juvenile steelhead. The scenario analysis shows that the modeled outcome varies by up to 50% depending on the scenario and is particularly sensitive to the location and magnitude of uncertainties in the model. This study informs future field monitoring efforts to develop flow-ecology relationships and promotes effective translation and modeling of existing flow-ecology relationships and their uncertainties.

(101 pages)

PUBLIC ABSTRACT

Accounting for Critical Attributes and Uncertainty in Flow-Ecology Relationships

Elizabeth Decker Morgan

Environmental flows are used to maintain streamflow for aquatic species in rivers while also sustaining human water requirements. While there are many approaches to develop environmental flows, they all rely on a strong conceptual understanding of flow-ecology relationships, which are often uncertain. Uncertainty in flow-ecology relationships can stem from using limited data to develop or test relationships or an incomplete understanding of the attributes inherent to each relationship, such as climate and land conditions. Accounting for these attributes and uncertainty in flow-ecology relationships is critical given mounting interest to develop and implement environmental flows at large scales, often with limited information. Using the South Fork Eel River watershed in northern California USA as a case study, I explored attributes and uncertainty in flow-ecology relationships through a targeted review of academic journal articles and Bayesian Network modeling. I found that few relationships describe explicit links between the flow regime and species or cover the full range of climate and land conditions present in the watershed. These gaps informed several scenarios within a Bayesian Network model—represented as different sets of probabilities—which show that model results can differ by up to 50% depending on the uncertainty scenario. This study informs future field monitoring efforts to develop flow-ecology relationships and

promotes effective translation and modeling of existing flow-ecology relationships and their uncertainties.

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Betsy Morgan

CONTENTS

Page

LIST OF TABLES

Page

LIST OF FIGURES

Page

INTRODUCTION

It is widely understood that key components of the natural flow regime and associated physical conditions and processes, such as water temperature and sediment regime, are critical for sustaining aquatic species (Poff, 2018; Poff et al., 1997; Yarnell et al., 2020). For example, anadromous salmonids rely on flow as a biological trigger for spawning and migration and have specific physical habitat requirements related to stream temperature and spawning substrate (Bjornn & Reiser, 1991). Flow variability also influences species composition. In seasonal climates, native species adapted to variability can withstand naturally stressful conditions that invasive species cannot (Gasith & Resh, 1999). Aquatic ecosystems now face a range of stresses from anthropogenic activities that alter the natural flow regime and associated physical habitat conditions, including water diversions, hydropower, and flood control (Gangloff et al., 2016; Gibeau, Connors, & Palen, 2017; Tonkin et al., 2018). These human activities, coupled with current and anticipated effects of climate change, are contributing to loss of aquatic biodiversity and ecosystem services (Häder & Barnes, 2019; Tickner et al., 2020; Tonkin et al., 2019).

Natural resources agencies are addressing these hydrologic alterations in part by developing and implementing environmental flows (Arthington et al., 2018). Environmental flows are flow regimes provided to achieve a set of desired ecological outcomes—defined as a species or process that is of management interest and that can be maintained through flow management—while also sustaining human water requirements (Arthington et al., 2018). A variety of approaches are commonly used to develop environmental flows, which all use different methods, assumptions, and data requirements (Tharme, 2003). For example, the Tessman method (Tessman, 1979) is based on average annual and monthly natural flows (prior to substantial anthropogenic impacts), while the Functional Flows method (Escobar-Arias & Pasternack, 2010; Yarnell et al., 2015, 2020) focuses on maintaining key aspects of the natural flow regime known to support a suite of critical ecological, geomorphic, and biochemical processes (e.g., peak flows, spring recession flows). While methods vary widely, all approaches are similar in that ecological outcomes are characterized in part by the expected ecological response to streamflow, or flow-ecology relationships (Horne et al., 2019). Therefore, flow-ecology relationships are fundamental for developing and adaptively managing environmental flows (Horne et al., 2018).

There is growing recognition that improved conceptual understanding of how streamflow affects aquatic and riparian species, either directly or through mediating physical conditions (e.g., sediment composition, water temperature, hydraulic conditions) or biological factors (e.g., food web dynamics), is critical to developing environmental flows that achieve specific ecological outcomes (Arthington et al., 2010; Holmes et al., 2018; Poff, 2018; Yarnell et al., 2020). To address this gap, researchers are increasingly employing conceptual and Bayesian Network (BN) models to portray inferred causal links between flow and ecological outcomes and to evaluate alternative flow management decisions with respect to these outcomes (Horne et al., 2018). Causal links can be defined using conditional probabilities, which specify how a variable (e.g., water temperature) is expected to respond given a change in an associated variable (e.g., summer baseflow) (Horne et al., 2018). For example, Stewart-Koster et al. (2010) used a hypothetical BN model to estimate the likelihood of low dissolved oxygen events based on expert understanding of water velocity and riparian cover. BN models are popular because they incorporate a variety of information types (Castelletti & Soncini-Sessa, 2007) and inherently represent uncertainty through probability distributions (Chen & Pollino, 2012; Uusitalo, 2007). They are commonly used to compare expected ecological outcomes (e.g., spawning of a native fish) under alternative water management decisions (Horne et al., 2018). For instance, Shenton et al. (2011) used BN models to depict the spawning and recruitment potential of two native fish under different frequencies and magnitudes of seasonal flow events to inform development of environmental flows under different climate conditions.

Despite recent contributions of BN modeling to environmental flows applications, opportunities remain to improve how these models are applied to understand flow-ecology relationships and uncertainties in these relationships. Uncertainty—defined as any departure from a complete understanding of a system—can result from inherent variability, incomplete knowledge, or both (Horne et al., 2017; Walker et al., 2003). While uncertainty has many dimensions (Walker et al., 2003), it can be generally categorized using four levels that extend from a known range of values (Level 1) to deep uncertainty (Level 4) (Courtney, 2003; Riesch, 2013; Marchau et al., 2019; Wang et al., 2020). Because river ecosystems are inherently complex, it is common for interactions between variables to be unknown or poorly understood (Williams et al., 2019). In these instances, BN models may produce inconclusive results (e.g., Shenton et al., 2011) or fail to accurately communicate uncertainty beyond a single probability distribution, or Level 2 uncertainty. Thus, an approach is needed that allows Level 3 uncertainty, or uncertainty scenarios with no known likelihood, to be incorporated within BN modeling of natural systems.

In addition to identifying the level of uncertainty, it is important to understand the attributes—defined as characteristics that are inherent to a system or thing— that underpin relationships within a BN model. For flow-ecology relationships in particular, uncertainty can derive from (i) using limited data to develop or test relationships and/or (ii) an incomplete understanding of the attributes inherent to each relationship, such as the geomorphic setting, climate, antecedent conditions, or other critical controls (e.g., Lynch et al., 2018; Walters, 2016). These attributes are fundamental for informing the boundaries of a model and identifying issues that can be addressed using the model and relationships (Walker et al., 2003). While some studies have used literature reviews to improve understanding of flow-ecology relationships (e.g., Greet et al., 2011; Miller et al., 2013; Poff & Zimmerman, 2010) and subsequently inform BN modeling efforts, there is an additional need to consider the attributes that underpin these relationships, including the spatial, temporal, and physio-climatic conditions. Accounting for these attributes and uncertainty is critical given mounting interest to develop and implement environmental flows at catchment or larger scales with limited information to address widespread and rapid degradation of river ecosystems (Arthington et al., 2018).

The overall purpose of this thesis is to evaluate and represent critical attributes and uncertainty in flow-ecology relationships to facilitate development of effective environmental flows on all streams and rivers in a watershed. The first objective is to <u>identify flow-ecology relationships and their associated attributes and uncertainties within an intensively studied watershed using a systematic review of peer-reviewed flow-</u>

ecology studies. The second objective is to improve representation of different levels of uncertainty in flow-ecology relationships by combining traditional BN modeling with scenario analysis. This approach is novel because it characterizes flow-ecology relationships and identifies attributes of each relationship that are critical for successfully applying relationships within a management setting. This research also presents an approach for representing Level 3 uncertainty in flow-ecology relationships while still using established and accessible tools, like BN models. The review process and uncertainty modeling approach can be adapted and applied to other locations and natural resources issues beyond environmental flow management.

STUDY AREA

Research objectives were addressed in an application to the South Fork Eel River (SFER) watershed in coastal northern California, USA. The SFER watershed spans 1,785 square kilometers of Humboldt and Mendocino counties (California Department of Fish and Wildlife, 2014). As depicted in Fig. 1, seven distinct channel reach types exist within the SFER watershed that were previously determined using hierarchical clustering of reach-scale field surveyed geomorphic characteristics (e.g., slope, bankfull depth) (Byrne et al., 2020). These channel types range from high width-to-depth streams with riffle-pool morphology (SFE01) to confined and high-gradient step-pool streams (SFE07) (Fig. 1). Like much of California, the SFER watershed has a Mediterranean climate characterized by cool wet winters and warm dry summers (Aschmann, 1973; Gasith & Resh, 1999). As a result, the flow regime is highly seasonal with distinct high flow and low flow seasons as well as immense inter-annual variability. Aquatic species in Mediterranean climates are adapted to the seasonal flow regime and possess life history strategies that help them persist in periods of flooding and low flow conditions (Bonada & Resh, 2013; Gasith & Resh, 1999). However, the seasonality of flow creates competition for water in dry summer months, which makes these regions susceptible to flow alteration by humans and associated habitat impairments (Gasith & Resh, 1999). Furthermore, unpermitted irrigation diversions—primarily for cannabis—are prevalent in the SFER watershed (California Department of Fish and Wildlife, 2014), which is leading to growing concern over adequate streamflow and suitable habitat for aquatic species over the summer low flow period (California Department of Fish and Wildlife, 2016).

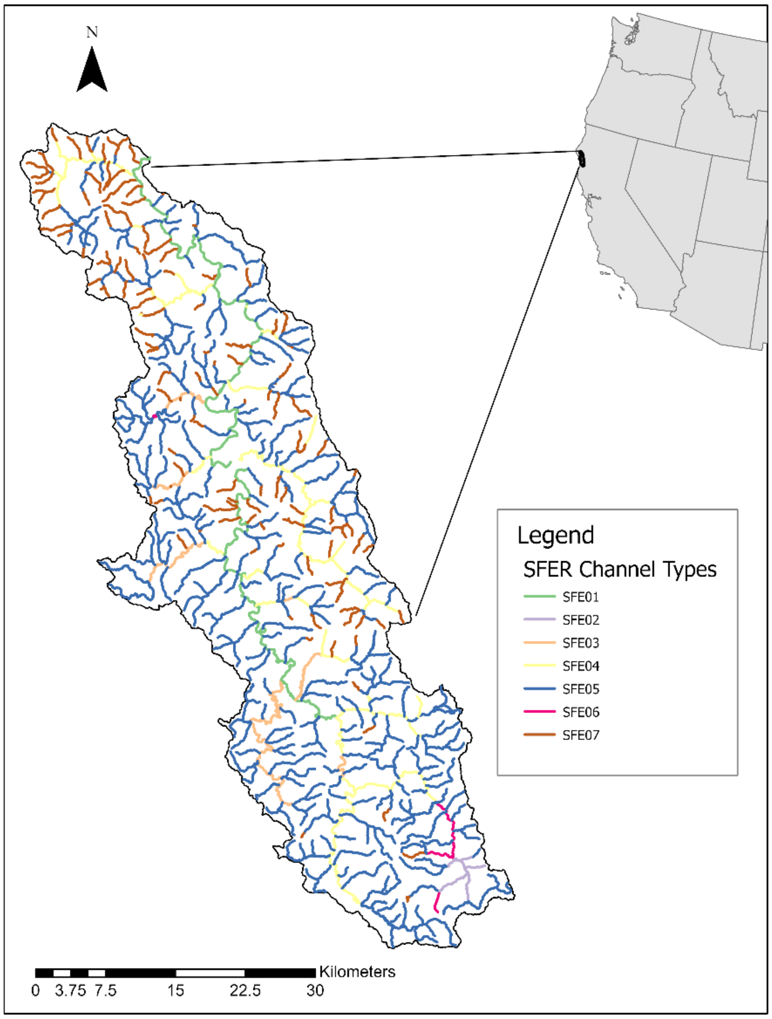


Fig. 1. South Fork Eel River (SFER) watershed in coastal northern California, USA. Geomorphic channel types include confined high width-to-depth, gravel cobble, riffle-pool (SFE01), unconfined, gravel, riffle-pool (SFE02), confined, gravel-cobble, bed-undulating (SFE03), confined, high width-to-depth, gravel-boulder, uniform (SFE04), confined, low width-to-depth, gravel-cobble, uniform (SFE05), partly-confined, gravel-cobble, uniform (SFE06), and confined, high-gradient, cobble-boulder, step-pool/cascade (SFE07).

In 2014, the California State Water Resources Control Board and the California Department of Fish and Wildlife were directed by the California Water Action Plan to enhance instream flows for anadromous fish in five priority watersheds, including the SFER. Anadromous species of concern within the SFER watershed include the Southern Oregon/ Northern California Coast coho salmon (fall-run), California Coastal chinook salmon (fall-run), and the Northern California steelhead (winter-run and summer-run) (Moyle et al., 2017). Populations for all species have declined in recent years, and as a result, all strains of salmonids are listed as threatened on the federal endangered species list (California Department of Fish and Wildlife, 2014). However, the SFER watershed remains an important stronghold for northern California strains of salmonids. For example, it supports the largest population of wild Southern Oregon/ Northern California Coast coho salmon (Moyle et al., 2017).

In addition to providing instream flows for anadromous fish, the State Water Resource Control Board and California Department of Fish and Wildlife must protect river ecosystems from negative impacts of cannabis cultivation under Senate Bill 837. Required actions include developing and setting environmental flows that maintain natural flow variability and flow conditions for all fish life stages (e.g., spawning, migration, rearing). In response to both mandates, the two agencies are collaborating with other stakeholders to develop environmental flows across the SFER watershed to maintain native salmonids, other aquatic species (e.g., amphibians, mussels, algae), and required habitats. Stakeholders plan to use watershed characteristics such as water year type (WYT) (California Department of Fish and Wildlife, 2020) and geomorphic channel type (Guillon et al., 2020) to organize management efforts through time and space across the SFER and other coastal northern California watersheds. For example, environmental flows could be conditional on whether the area is experiencing a wet or dry year.

SFER natural resource agencies and stakeholders are actively compiling existing information related to flow-ecology relationships to inform development of environmental flows. However, there have been no systematic efforts to assess the existing body of SFER flow-ecology literature in a way that could improve conceptual understanding of flow-ecology relationships. Furthermore, there is a need to understand how the specific attributes inherent to relationships (e.g., channel type, WYT) influence how they are applied across the watershed.

METHODS

Systematic Literature Review

The purpose of the literature review (objective 1) was to compile peer-reviewed studies that relate directly to the SFER watershed and pertain to flow, in-stream physical conditions, and desired ecological outcomes for the watershed (e.g., salmonids, amphibians). The key steps to systematically review the flow-ecology literature are illustrated in Fig. 2, including identifying relevant peer-reviewed studies within the SFER watershed and recording and visualizing categorical, temporal, and spatial attributes of flow-ecology relationships across the studies.

Identify Flow-Ecology Studies

The set of studies considered was selected through a systematic search process of peer-reviewed journal articles in the database Scopus and included articles published by May 26th, 2020. Since the goal was to return papers pertaining to the SFER watershed, the initial keyword-abstract-title search criteria used in Scopus was: “South Fork of the Eel River” OR “South Fork Eel River” OR “Eel River Basin.” This search resulted in 91 articles.

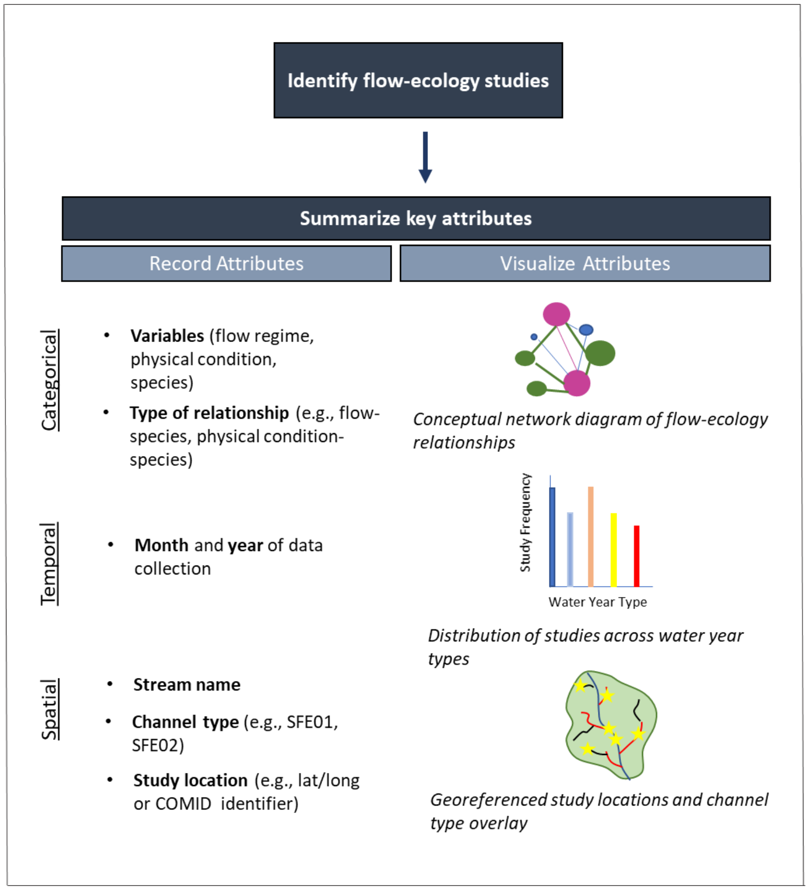


Fig. 2. Methods overview for Objective 1. Key steps include to identify peer-reviewed flow-ecology studies within the SFER watershed and record and visualize categorical, temporal, and spatial attributes across studies.

Of the initial 91 articles identified in the SFER, 25 described riverine relationships within the following categories: flow – species, flow – physical condition, species – species, physical condition – species, physical condition – physical conditions, or species – physical condition. In this case, "flow" describes characteristics of the flow regime (e.g., duration, timing, magnitude) or seasonal flow components (e.g., summer baseflow, peak flows). Physical condition describes variables that may be affected by flow, such as water temperature, sediment composition, channel morphology, or hydraulic conditions. Forward and backward citation chaining (e.g., Jalali & Wohlin, 2012) was then used to identify any additional articles cited by or within these 25 studies that met the same criteria. Articles were selected even if there was uncertainty about whether they belonged in a category. This process resulted in 109 studies which were further reduced to 66 studies based on re-application of the initial search criteria. Most studies did not reference the SFER watershed in their abstract, title, or keywords, which means they were not returned in the initial search. Dissertations, theses, grey literature, and studies that collected no new data (e.g., review articles) were excluded from the literature review. Flume and laboratory experiments were only included if they used species sourced directly from the SFER watershed.

Summarize Key Attributes

Next, studies were read to extract key attributes expected to improve the conceptual understanding of flow-ecology relationships and identify research gaps. The attributes fell into three groups. The first group consisted of categorical attributes related to the types of relationships and relationship variables, as described below. The second group included temporal attributes, such as the dates of data collection, which were used to understand the distribution of relationships across seasons and WYTs. The final group included spatial attributes, such as the location and stream name where data collection occurred, which helped characterize the spatial coverage of flow-ecology relationships across the watershed. Relationship attributes were recorded in Excel and coded in the qualitative software ATLAS.ti (Version 8.4; ATLAS.ti Scientific Software Development

GmbH, 2019) according to the protocols in Appendix A. Data were then analyzed and visualized using R (Version 3.5.1; R Core Team, 2018) and ArcGIS Pro (Esri Inc., 2020).

Categorical Attributes

Categorical attributes of interest were defined based on prior knowledge of management interests and ecological outcomes within the SFER watershed (Table A1, A2). Categorical attributes include the relationship type (e.g., flow – species, physical condition – species) and variables that pertain to flow (e.g., dry-season baseflow, spring recession), physical conditions (e.g., depth, velocity, shear stress, temperature), and species (e.g., steelhead, algae, salamander) within each relationship. Flow regime characteristics (e.g., duration, frequency, magnitude) were specified for each flow variable and life stages (e.g., seedling, juvenile, adult) and interactions (e.g., breeding, predation, feeding) were specified when possible for relationships pertaining to species.

Attribute code-co-occurrence tables from ATLAS.ti were exported and used to calculate summary statistics for categorical attributes, which portray the distribution of relationship types and variables across SFER relationships. The categorical attributes were used to create a conceptual network diagram of links between variables (independent to dependent) using the R package “igraph” (Csardi & Nepusz, 2006). Relationships with more than one attribute entry (e.g., light to algae and macroinvertebrates) were split into multiple links (e.g., light to algae, light to macroinvertebrates). Therefore, the conceptual network contains several expanded relationships and represents the availability of information across relationships.

Temporal Attributes

Inter-annual flow variability significantly affects ecological outcomes in many systems (e.g., Lynch et al., 2018). Because flow variability and seasonality are fundamental to Mediterranean river ecosystems (Gasith & Resh, 1999), they are expected to play a pivotal role in flow-ecology relationships in the SFER. As such, the start and end date of data collection for each relationship were recorded to help describe the temporal coverage of relationships. These attributes were analyzed to assess the seasonality of data collection and representation of WYTs within and across relationships.

Daily average streamflow at the unimpaired Elder Creek USGS gage (USGS 11475560) was used to calculate the reference WYTs for the watershed. Five WYTs (i.e., very dry, dry, moderate, wet, very wet) were defined by sorting cumulative annual flow into quintiles over the period of record (1967–2019). The WYTs were assigned to relationships according to the water year of the start date and subsequent years of data collection. This method was used to be consistent with several studies in the literature review (e.g., Kelson & Carlson, 2019) and SFER water managers; however, other water year typing approaches exist in California. For example, the California Environmental Flows Framework classifies WYTs using uniform terciles (California Environmental Flows Working Group, 2020) and other approaches exist to support WYT classifications within nonstationary climates (Null & Viers, 2013; Rheinheimer, Null, & Viers, 2016).

Binary presence and absence counts of WYTs included in the development of each flow-ecology relationship were used to determine the number of unique WYTs encompassed within a relationship and the total composition of WYTs across relationships. For example, a relationship identified from a study that spanned two dry years and one wet year would count as two unique WYTs and would contribute one count each (dry and wet) toward the total WYT composition. This approach was used instead of counting the total number of years in each WYT (per relationship) because the focus was on the representation of relationships across climate conditions rather than sample size.

Spatial Attributes

Data collection locations for each flow-ecology relationship were recorded to characterize the spatial coverage and resolution of relationships across channel types, which is the spatial management unit used by SFER agencies. Using ArcGIS Pro, data collection locations were spatially referenced to reach segments of the channel type shapefile (Guillon et al., 2020) using coordinates or maps provided within the studies. The common identifier of the NHD feature (COMID) and the associated channel type classification (SFE01–SFE07) were recorded for the reach segments where data collection occurred. A segment indicates that data were collected in the vicinity of the reach and does not represent the density or method of data collection (i.e., points versus transects). Reach segments were recorded based on the spatial resolution provided within each study.

Similar to the WYT analysis, binary presence and absence counts of channel types included in the development of each flow-ecology relationship were used to determine the number of unique channel types encompassed within a relationship and the total composition of channel types across relationships. The location of relationships across the watershed was visualized in ArcGIS Pro by manually creating polylines for individual relationships based on the COMIDs. The line density tool was used to produce a raster (150 m cell size) that visualizes the relative density of data collection for peer-reviewed flow-ecology studies across the watershed in length per unit area (km/km^2). The line density tool sums the length of segments where data collection occurs and divides the total by a search area (radius = 1240 m^2).

Bayesian Network Model and Scenario Analysis

The major steps for objective 2 are depicted in Fig. 3. The first step was to use information obtained from flow-ecology studies in objective 1 to develop an exploratory conceptual model for a target species and life stage in the watershed (i.e., ecological outcome). Since the aim was to develop an approach for representing uncertainties related to specific ecological outcomes rather than developing a comprehensive model of the river ecosystem, which is outside the scope of this study, the conceptual model only includes select variables and relationships for a single species and life stage. The conceptual model was then transformed into a BN model by recreating it within modeling software (Netica, R), which required specifying BN model characteristics including node states (levels that describe possible conditions of a node) and conditional probabilities. BN model characteristics were informed using information collected in Objective 1 and the authors' judgement, which was applied when relationships and probabilities were not sufficiently described in the peer-reviewed studies. Finally, scenario analysis was performed to model the selected ecological outcome under 148 different sets of probabilities, which represent different uncertainties in flow-ecology relationships.

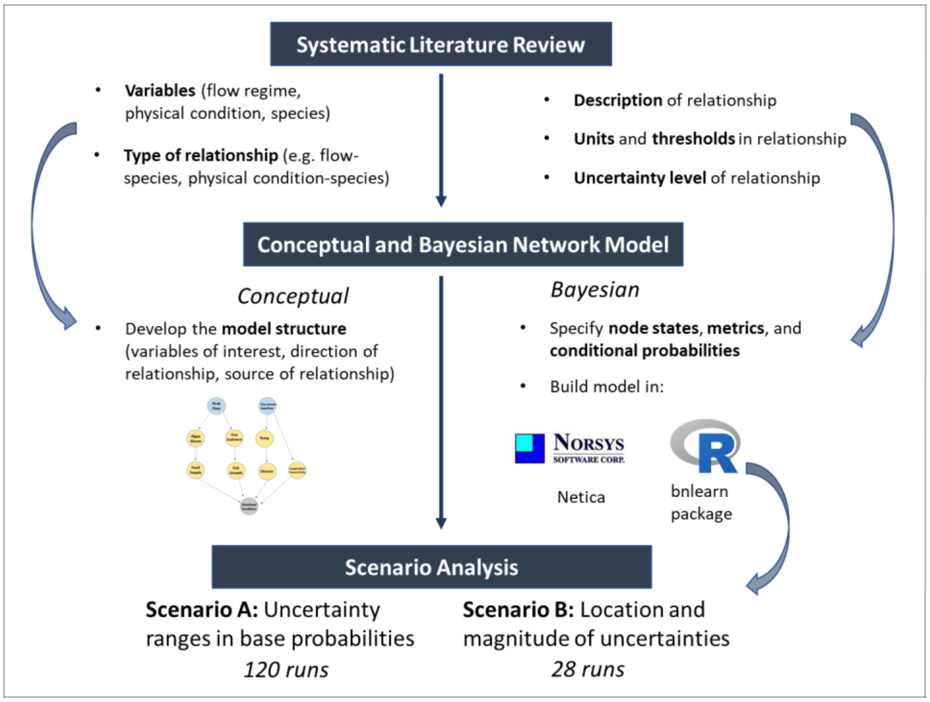


Fig. 3. Method overview for Objective 2. Major steps include using information from the systematic literature review (Objective 1) for the SFER watershed to inform a conceptual and BN model and performing scenario analysis using the BN model.

Systematic Literature Review

Additional attributes were extracted from studies to inform conceptual and BN modeling, including a short description of the methods and key findings for each relationship, as well as any specified units (e.g., m^3/s), thresholds (e.g., bankfull flow), or states (e.g., > bankfull flow) described in the relationship. Uncertainty in relationships was also ranked from Level 1 to 4 (low to high) (Courtney, 2003; Riesch, 2013; Marchau et al., 2019; Wang et al., 2020). Uncertainty can be based on a specific range of values (Level 1), a known probability distribution (Level 2), or several potential scenarios with no known likelihood (Level 3). For example, a Level 2 uncertainty is the likelihood of winter flows greater than bankfull and a Level 3 uncertainty is the composition of invasive fish to native fish within the SFER in 50 years. It is not possible to describe the highest level of uncertainty, or deep uncertainty (Level 4), using existing models and methods as it pertains to events that we have not experienced and have no understanding of (e.g., conditions in the intermountain west after the Yellowstone supervolcano erupts). Since uncertainty was unspecified in studies, the authors' judgement was used to classify levels for each relationship.

Conceptual and Bayesian Network Model

To develop the BN model structure, a preliminary conceptual model was created by linking key variables (e.g., flow regime, physical conditions) to the ecological outcome of interest according to a subset of flow-ecology relationships in the literature review. Based on information availability and conversations with stakeholders, juvenile steelhead was chosen as the target species and life stage for modeling efforts (i.e., ecological outcome) because they are more sensitive to habitat conditions compared to other species and life stages in the SFER watershed. All flow-ecology relationships were individually reviewed and organized based on whether they relate directly (e.g., mayfly are eaten by steelhead) or indirectly (e.g., algae biomass affects mayfly which are eaten by steelhead) to juvenile steelhead.

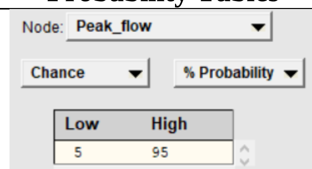
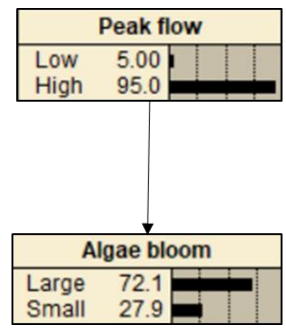
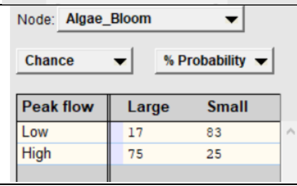
Fifteen studies were identified through this process and further condensed to the most prominent relationships following recommendations from Webb et al. (2012), who noted that excessive detail can dilute research efforts and conclusions. For example, individual relationships between algae and macroinvertebrates were condensed into a single relationship between algae and food supply and relationships covering detailed or obscure processes (e.g., species – species relationship between aquatic snails and steelhead) were removed. Key relationships that were not explicitly addressed through the literature review but are available elsewhere (e.g., winter flows scouring fine sediment) were specified through the authors' judgement.

Identified relationships were labeled in the conceptual model along with the relationship direction, uncertainty level, and position of variables in the model. The relationship direction refers to the causality of the relationship and was denoted by a positive or negative sign (Haraldsson, 2004). For example, a positive sign indicates that variables respond in the same direction (e.g., an *increase* in peak flow causes an *increase* in algae blooms) and a negative sign indicates a response in the opposite direction (e.g., an *increase* in fine sediment causes a *decrease* in fish growth). The variable position refers to its location in the model. Variables related to the flow regime (i.e., peak flow, dry-season baseflow) were categorized as independent hydrologic nodes, the ecological outcome (juvenile steelhead condition) was denoted as an end node, and all other variables were categorized as middle nodes. The term "node" is used in connection to BN modeling efforts where all variables are referred to as nodes. While simple, the conceptual model includes a range of ecosystem processes, habitat conditions, and seasonal hydrology experienced in the SFER watershed.

Next, the conceptual model was transformed into a BN model and used to represent understanding the ecological outcome based on uncertainty in flow-ecology relationships. The common BN modeling software Netica 6.05 (Norsy, 2018) was used. The first step was to recreate the conceptual model within Netica by adding nodes for each variable (e.g., summer baseflow) and linking related nodes to match the conceptual model structure. Within this node-link model, literature review findings were used to specify qualitative node states (e.g., high, low) and associated node state metrics (e.g., high = flows > bankfull). The ecological outcome modeled was juvenile steelhead condition—denoted using 'good' and 'poor' node states—which represents a qualitative aggregate measure of habitat and fish health nodes within the model. Based on the authors' judgement, a non-negative population growth rate could serve as a quantitative metric of good juvenile steelhead condition while a negative population growth rate would be associated with poor condition. All other node states and associated metrics are summarized in Appendix B (Table B1).

Finally, base probabilities were assigned in the form of conditional probability tables for each node. Probabilities for middle and end nodes were either assigned directly from a relationship in the peer-reviewed literature (e.g., probabilistic outcome from long-term data), informed by the literature but assigned based on the authors' judgement, or assigned completely by the authors' judgement when the relationship was not included in the literature review. Base probabilities and information sources for probabilities are included in Tables B10-B17. Table 1 provides an example of node states, metrics, and Netica conditional probability tables and model structure.

Table 1. Example BN model characteristics for peak flow and algae bloom nodes, including node states, metrics, conditional probability tables in Netica, and model structure in Netica.

Node	States	Metric	Netica Conditional Probability Tables	Netica Representation
Peak flow	Low High	< bankfull Q ≥ bankfull Q		
Algae bloom	Large Small	length ≥ 50 cm length < 50 cm		

The initial conditions for the model were determined by altering the probabilities in the two independent hydrologic nodes—peak flow and dry-season baseflow—to represent seasonality and interannual hydrologic variability in the SFER watershed, which are conceptually described in Power et al. (2015). Peak flow refers to flow events during the annual flood season that transport large amounts of sediment and restructure the channel and dry-season baseflow refers to summer low flows that dictate the extent and quality of inundated physical habitat (Yarnell et al., 2015). Since the hydrology in the BN model is described seasonally through two nodes whereas WYT is an annual climate condition, the hydrology was conceptually modeled using several sets of hydrologic conditions, which represent different probabilistic combinations of peak flow and dry-season baseflow. The Dry hydrologic condition consisted of a dry winter followed by dry summer, and the Wet condition consisted of a wet winter followed by wet summer. The probabilities for Wet and Dry conditions were specified at a 95% likelihood using the authors' judgement (e.g., 95% likelihood of high peak flow and high dry-season baseflow for Wet conditions). The Moderate condition had intermediate winter peak flow and dry-season baseflow probabilities, determined using 1.5- and 2-year flow recurrence intervals, respectively (Leopold, Wolmon, & Miller, 1964; Risley, Stonewall, & Haluska, 2008). Finally, Wet – Dry consisted of a wet winter (same as in Wet condition) followed by a dry summer (same as in Dry condition) to capture a common seasonal transition in the study area. The probabilities for each hydrologic condition are summarized in Appendix B (Tables B2-B9).

To facilitate the automation of multiple model runs for scenario analysis, the BN model was scripted in R using the bnlearn package (Scutari, 2010). Similar to Netica, the conceptual model structure was recreated by assigning nodes (e.g., peak flow, algae) to an empty graph and specifying a matrix of "from" and "to" links between the nodes. For example, the array c("PF", "Al") represents the link between peak flow and algae nodes. Node states were specified in similar arrays, for example, c("low", "high"). Next, conditional probabilities were imported into R through a series of .csv files and added to a matrix along with the node states to form individual conditional probability tables for nodes. Finally, the cpqueary command was used to calculate conditional probabilities for juvenile steelhead condition based on the evidence provided in the conditional probability tables. The cpqueary command uses a Monte Carlo approximation of 1 million runs, so the end probability varies slightly across runs. The BN model in Netica was used to verify the results of the R-based model.

Scenario Analysis

The main purpose of the scenario analysis was to explore different sets of probabilities in the BN model to understand how the system responds to Level 3 uncertainty. Traditional BN models represent uncertainty through a single probabilistic relationship (i.e., Level 2 uncertainty). However, this approach may underrepresent uncertainty for complex flow-ecology relationships where uncertainty cannot be understood as a single set of probabilities (i.e., Level 3 uncertainties).

Scenarios A and B explored Level 3 uncertainties in the BN model by varying the base probabilities in middle and end nodes (Fig. 4). The Base probabilities form the Base scenario, which assumes that uncertainty is adequately portrayed through a single set of probabilities. Scenario A tested uncertainty in the ability to specify a single, correct set of probabilities for relationships. In other words, I expect the base probability to be X, but it could fall between X1 (lower bound) and X2 (upper bound). Scenario A represents situations where (a) there is uncertainty in the true probability at a given location where relationships were derived, or (b) an existing relationship developed at one location is extrapolated to a different location where the direction of the relationships is known but the exact probability is not. For this scenario, lower and upper probability bounds were determined using the authors’ judgement and ranged from 0.1 below up to 0.2 above the base probability (Appendix B, Tables B18-B24). After probability ranges were identified for all middle and end nodes with Level 3 uncertainty, 30 random runs were performed by generating random numbers (with replacement) between the lower and upper probability bounds. The 30 unique sets of probabilities (A1, A2, A3, etc.) were each evaluated under the four hydrologic conditions, resulting in a total of 120 runs (Appendix B, Table B25). A Wilcoxon signed rank test for non-parametric paired data was used to test whether the ecological outcomes (likelihood of good or poor juvenile steelhead condition) were significantly different across uncertainty ranges and hydrologic conditions.

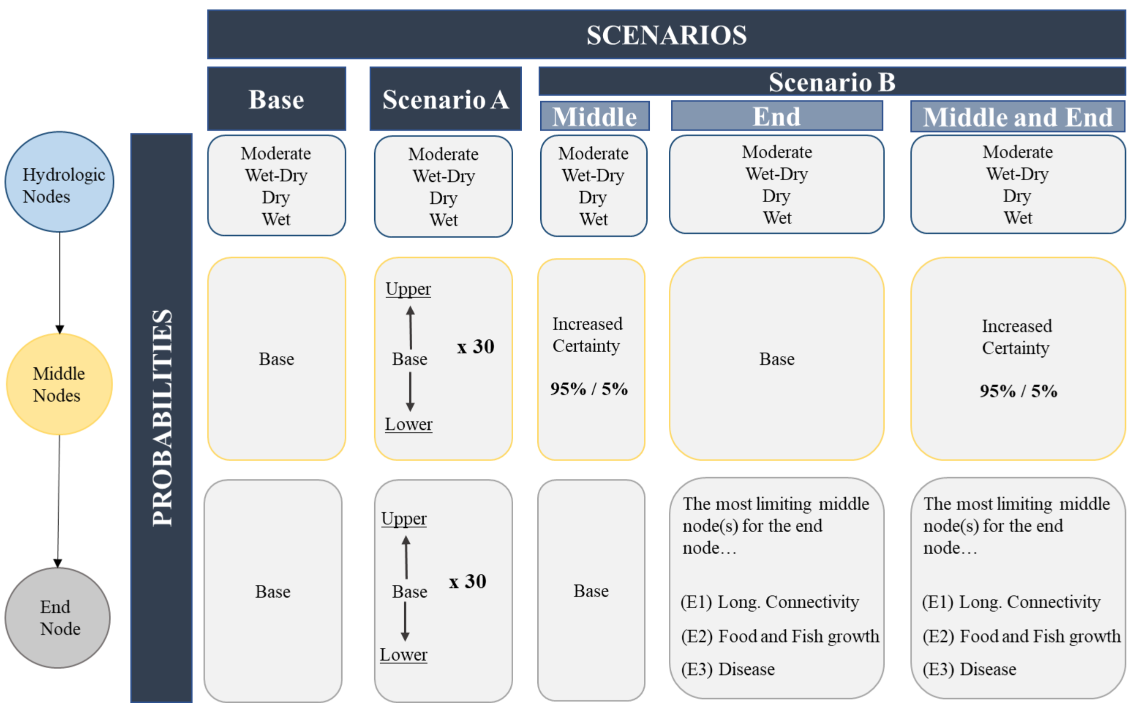


Fig. 4. Probabilities for hydrologic, middle, and end nodes in the BN model under the Base Scenario, Scenario A, and Scenario B.

Scenario B tested how the location and magnitude of uncertainty in the BN model influence the ecological outcome. This is relevant for understanding the management implications of missing or uncertain information and the conditions where uncertainty is more limiting. The first set of runs (Scenario B, Middle in Fig. 4) evaluated the effect of increasing certainty in the relationships between middle nodes. For example, the base probabilities of *high* and *low* temperature given *low* summer baseflow are 0.7 and 0.3, respectively. Under the “Increased Certainty” runs, the probabilities were changed to 0.95 (high) and 0.05 (low). Certainty was increased in this manner for all middle nodes exhibiting Level 3 uncertainties. The next three sets of runs (Scenario B, End in Fig. 4) evaluated uncertainty in our understanding of the variables that are most important or limiting for the ecological outcome, which is the end node in the BN model. The purpose of these runs was to explore how our understanding of an ecological outcome changes based on an incomplete or impartial understanding of management needs, given that it is difficult to isolate the individual importance of certain variables (Holmes et al., 2018). Therefore, end node probabilities were changed to evaluate the effect of having the most limiting variable be longitudinal connectivity (E1), food supply and fish growth (E2), or disease (E3). Finally, the third set of runs (Scenario B, Middle and End in Fig. 4) evaluated the pairwise combination of increasing certainty in the middle nodes and changing end node probabilities according to E1, E2, and E3. Each probability set was evaluated under the four hydrologic conditions for a total of 28 runs in scenario B (Appendix B, Tables B26-B32). The modeled results (likelihood of good and poor juvenile steelhead condition) were visualized using a heat map where each square represents the outcome under a scenario and hydrologic condition, which comprise a unique set of 64 probabilities.

RESULTS

Systematic Literature Review

Categorical Attributes

The final literature review resulted in 88 unique peer-reviewed flow-ecology relationships pertaining to the SFER watershed. 49% of all relationships fell under the physical condition – species category, and the next most common category was species – species relationships (33%). Only 15% of relationships were categorized in the flow – species category and 3% made up the categories of physical condition – physical condition and species – physical condition. Although several relationships discussed how flow indirectly affects species through mediating physical conditions (e.g., temperature, velocity), no specific relationships between flow and physical conditions were identified.

There was unequal research across flow, species, and physical condition variables within flow-ecology relationships. Algae (17.5%), Aquatic Macroinvertebrates (17.5%), Foothill Yellow Legged Frog (FYLF, 16%), and Steelhead (16%) made up 67% of all species discussed. The following species each encompassed 1–4% of all relationships: aquatic snail, bull frog, cyanobacteria, lamprey, mussel, native misc. fish, pacific tree frog, pikeminnow, salamander, sculpin, terrestrial macroinvertebrates, and vegetation. There were no relationships for coho or chinook salmon in the peer-reviewed studies pertaining to the SFER watershed. Fifty-six percent of explicitly identified life stages across species were juvenile and 44% were adult. Of the interactions that were explicitly identified in relationships, 47% discussed a feeding relationship (e.g., predation, food webs) and 4% discussed predation by an invasive species. Rearing (26%) relationships were more frequent than breeding (19%) or migration (4%) relationships.

Within physical condition – species relationships, water temperature was most common (27%) followed by general habitat (15%), which describes a relationship related to three or more physical conditions. The general habitat condition was commonly used for multi-species relationships, such as a physical habitat assessment for a native fish assemblage. Velocity (12%) and nutrients (10%) were the next most common physical conditions, followed by geomorphic (i.e., contributing area, 8.5%), light (8.5%), depth (7%), dimensionless relationships (i.e., unitless, 5%), sediment (3%), width (2%), and shear stress (2%). While many relationships were indirectly related to the flow regime (i.e., a physical condition – species relationship developed during baseflow period), only 13 relationships included direct links to the flow regime. Peak flow (40%) and the spring recession (40%) were the most represented flow components, followed by dry-season baseflow (13%) and wet-season initiation flows (7%). Flow was often described by magnitude (65%) and was explicitly described in terms of WYT 23% of the time. Timing was used twice (12%) to describe flow and there were no relationships explicitly described in terms of duration or frequency.

The conceptual network diagram highlights the disproportionate amount of information present within SFER peer-reviewed studies on aquatic species and physical conditions compared to flow (Fig. 5). The most well studied relationship (ten relationships total) is between water temperature and the FYLF. Other well-studied relationships include species – species relationships related to algae and aquatic macroinvertebrates, and the relationship between physical conditions and algae. The most well studied flow – species relationships are the spring recession to FYLF and peak flow to algae.

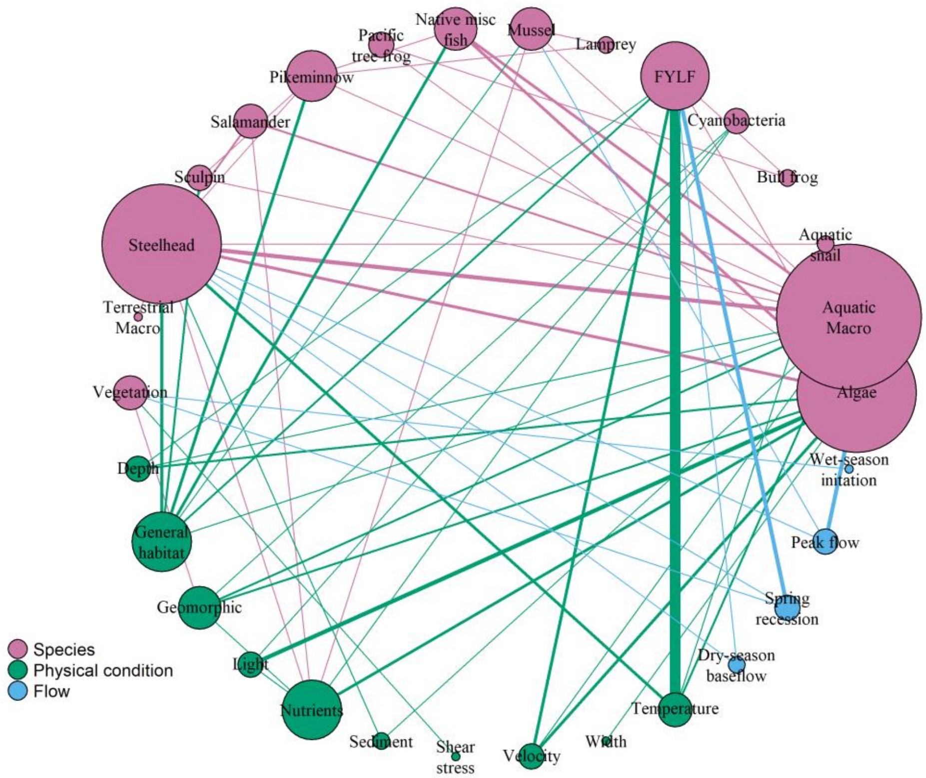


Fig. 5. Conceptual network model of flow-ecology information for peer-reviewed studies in the SFER watershed. Larger nodes indicate that variables were included more often in relationships and thicker lines mean there is more information available for a relationship.

Temporal Attributes

Most flow-ecology relationships were developed using data collected during summer months (Fig. 6b). In fact, 57% of relationships used data that fell solely within

June through September, which coincides with low streamflow volumes (Fig. 6a). An additional 23% of studies (80% total) used data spanning May through October. Within any given year, few relationships collected data over periods longer than 180 days (10%) and only 8% used data collected in November, December, and January.

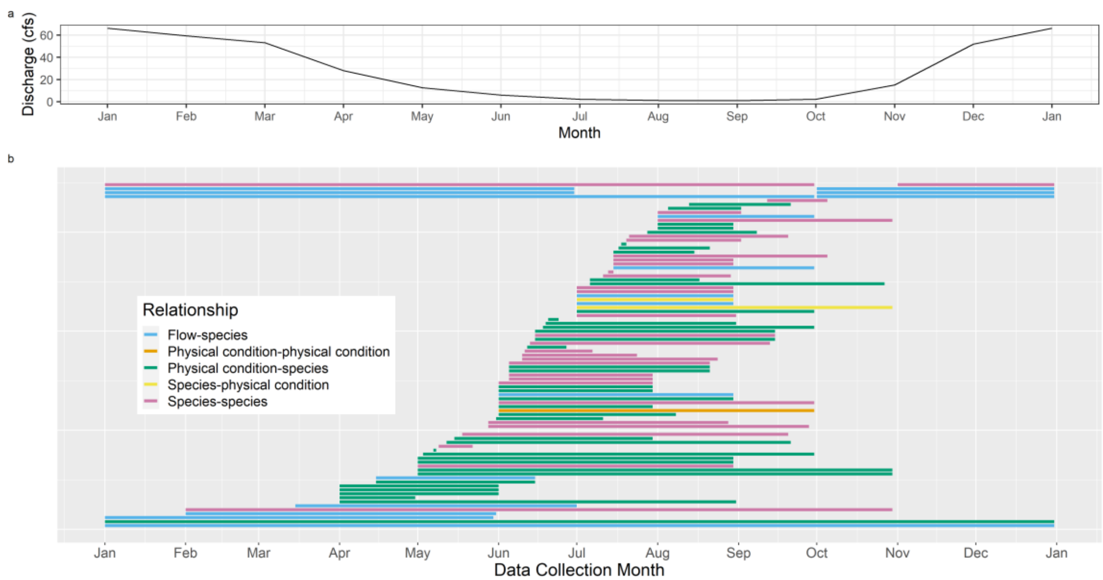


Fig. 6. (a) The mean of monthly streamflow at Elder Creek (USGS 11475560) from 1968–2019 and (b) the seasonality of data collection in SFER flow-ecology relationships.

The number of unique WYTs used to develop flow-ecology relationships follows a right-skewed distribution (Fig. 7a). Fifty-six relationships (~65%) were developed using data that spanned only one of five possible WYTs, 13 relationships (15%) were developed from data collected across two WYTs, and few relationships were developed across more than two unique WYTs (Fig. 7a). Fig. 7a illustrates the specific WYTs used to develop each relationship, organized by the number of unique WYTs represented. The total composition of WYTs across all relationships is more equally distributed, with very dry and dry WYTs slightly more common than wet or very wet (Fig. 7b).

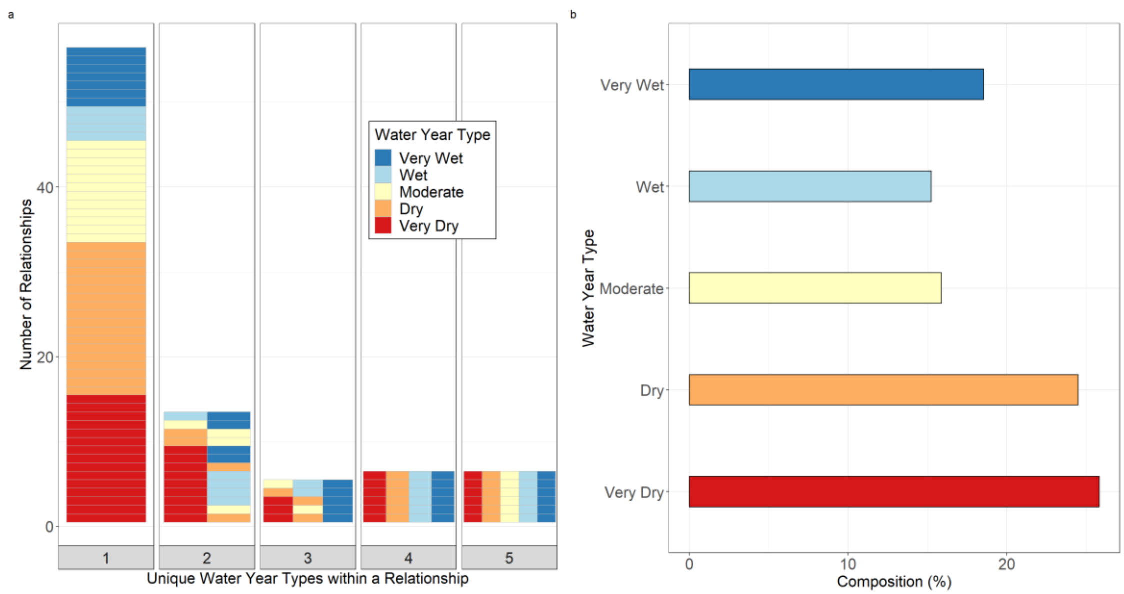


Fig. 7. (a) The number of relationships across unique WYTs and (b) the total composition of WYTs across relationships.

Spatial Attributes

Similar to the distribution of WYTs, the distribution of unique channel types across relationships is also right skewed (Fig. 8a). Sixty-four relationships (74%) were developed using data collected from only one channel type and 18 relationships (21%) used data spanning two channel types (Fig. 8a). Few relationships were developed across three, four, or five channel types, and no relationships spanned all seven channel types present within the SFER watershed. Across all relationships, channel types SFE04 (confined, high width-to-depth, gravel-boulder, uniform) and SFE05 (confined, low width-to-depth, gravel-cobble, uniform) were most common and made up 58% and 30% of the channel types represented, respectively (Fig. 8b).

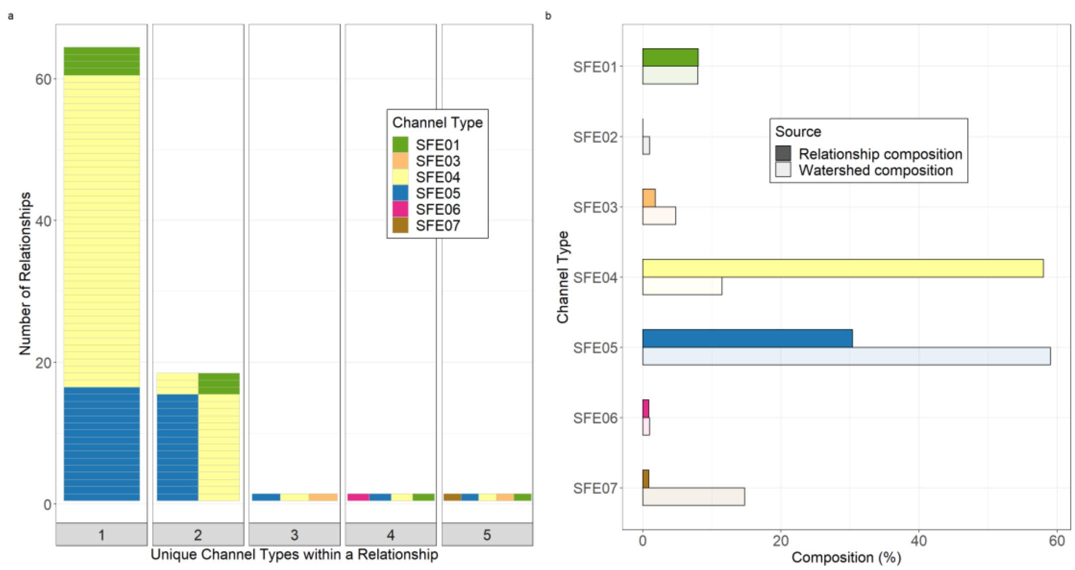


Fig. 8. (a) The number of relationships across unique channel types and (b) the total composition of channel types across relationships (dark shade) and within the watershed (light shade). Channel type descriptions are provided in the text.

Data collection is spatially clustered within the SFER watershed and occurs in high density throughout public lands (e.g., state parks) and research reserves (Fig. 9). The density of data collection is greatest near the southern end of the watershed in the Angelo Coast Range Research Reserve—a pristine environment with cool, groundwater fed tributaries and high quality habitat where local researchers have focused significant data collection for decades (e.g., California Department of Fish and Wildlife, 2014; Greer et al., 2019; Wang et al., 2020). This research reserve contains channel types SFE04 (high width-depth, gravel-boulder streams) and SFE05 (low width-depth, gravel-cobble streams), which likely contributes to the high representation of these geomorphic settings across relationships despite their actual composition in the watershed (Fig. 8b). The next highest density of data collection occurs in the northern sub basins, which have lower quality habitat due to logging and grazing in the past (California Department of Fish and Wildlife, 2014). This area encompasses Humboldt Redwoods State Park and has a range of channel types including mainstem (SFE01, SFE04) and tributary (SFE05, SFE07) settings. Data collection also occurs along the mainstem SFER, which parallels a highway and intersects several small towns.

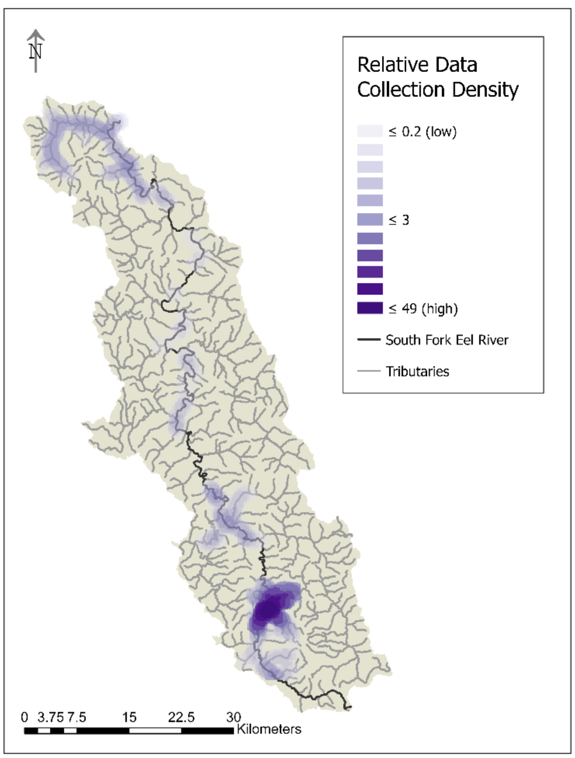


Fig. 9. Relative density (km/km^2) of data collection within peer reviewed flow-ecology studies in the SFER watershed.

Bayesian Network Model and Scenario Analysis

Conceptual and Bayesian Network Model

The conceptual model developed from the flow-ecology literature review includes 10 variables: two hydrologic nodes (blue), seven middle nodes (yellow), and one end node (grey) (Fig. 10). Four relationships were informed directly from studies in the literature review (Marks et al., 2000; Power et al., 2008; Schaaf et al., 2017; Suttle et al., 2004) and the remaining relationships were informed by the authors' judgement. Only one relationship was considered at Level 2 uncertainty (solid line) and the remaining were evaluated as Level 3 uncertainty (dashed line) (Fig. 8). The relationship between peak flow and algae was considered at a Level 2 uncertainty since it was based on a probabilistic relationship developed from 18 years of field data by Power et al. (2008).

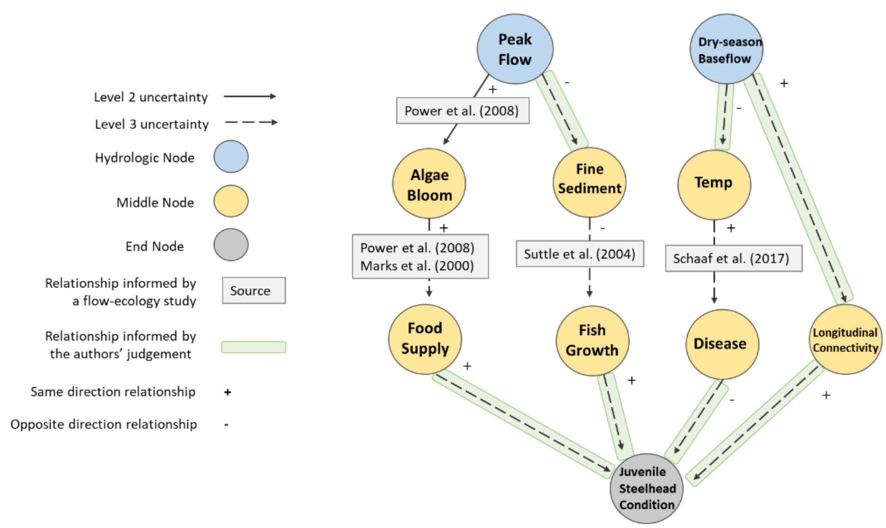


Fig. 10. A conceptual model for juvenile steelhead condition informed by the authors' judgement (green outline) and regional flow-ecology studies (grey squares). The color of the node indicates the position in the model, the plus (+) and minus (-) signs indicate the direction of the relationship, and the line type (dashed or solid) indicates the uncertainty level of the relationship.

The conceptual model depicted in Fig. 10 does not attempt to represent the entire river ecosystem and contains many ecological simplifications to facilitate BN modeling and scenario analysis. BN models have a limited ability to account for cyclical loops and feedbacks (Hart & Pollino, 2009; Uusitalo, 2007), so such relationships were not included. For example, the conceptual model only depicts a continuous positive relationship with algae and food supply and does not represent the feedback that occurs when algae blooms reach a level where oxygen depletion occurs, which negatively affects aquatic species (e.g., Power et al., 2015). In addition, the conceptual model was informed heavily by the SFER peer reviewed literature and the authors' judgement related to select variables, so it does not include all possible relationships and variables that may affect juvenile steelhead. Alternative conceptual models will result from changing the structure of the existing model (i.e., relate food supply and temperature to fish growth) or by adding additional variables (i.e., invasive species predation, riparian cover). This concept of model structure uncertainty dictates that many realistic models exist depending on the dominant relationships, variables, and boundaries identified by the modeler (Walker et al., 2003)—only one of many possible models was explored herein as a simple case of study.

The same conceptual model structure is reflected in the Netica-based BN model in Fig. 11, which shows the likelihood of good and poor steelhead condition under the dry hydrologic condition (i.e., low peak flow and low dry-season baseflow) and base probabilities. Under these conditions, the likelihood of good steelhead condition is 39.3% and the likelihood of poor condition is 60.7%. The likelihood that juvenile steelhead condition is predominantly good (> 50% good condition) or poor (> 50% poor condition) depends on the conditions of related nodes.

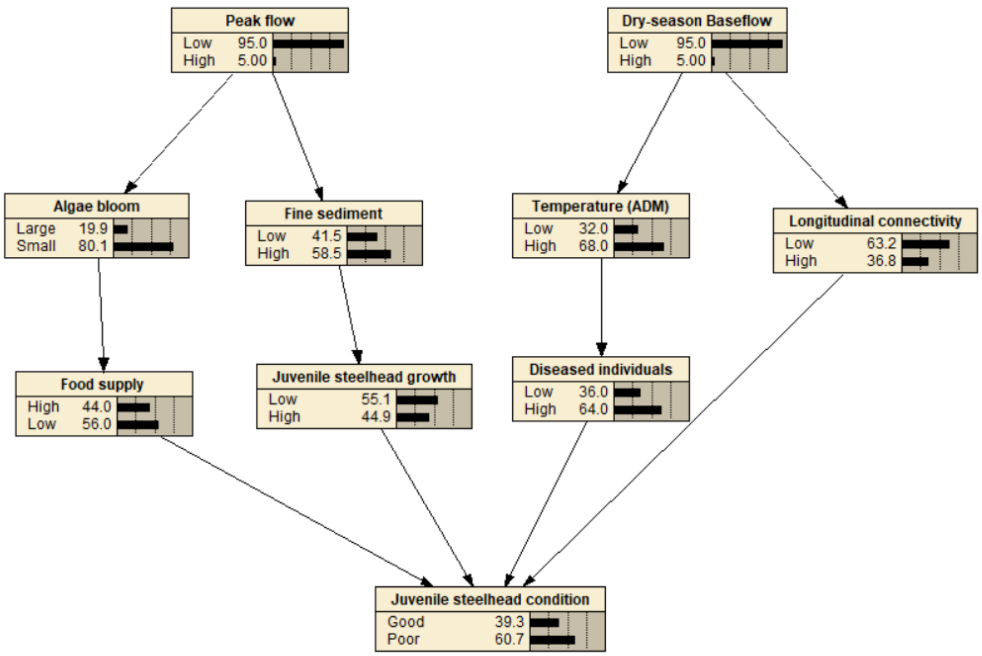


Fig. 11. Bayesian Network model created in Netica for juvenile steelhead condition under base probabilities and dry hydrologic conditions.

Scenario Analysis

When ranges of base probabilities were explored in Scenario A, the likelihood of good or poor steelhead condition only varied by an average of 10% within a given hydrologic condition (Fig. 12). While this range was consistent across model runs, the magnitude of outcome diverged across hydrologic conditions. The probability of achieving good and poor outcomes is not statistically different under Moderate hydrologic conditions ($p = 0.95$). In fact, nearly half of the Moderate runs resulted in a poor outcome, indicating that the model cannot consistently predict steelhead condition under Moderate hydrologic conditions. This is further illustrated by the overlapping probability distributions in the box and whisker plots (Fig. 12). While the outcomes were statistically distinct ($p<0.001$) under Wet – Dry, Wet, and Dry conditions, only the Wet and Dry conditions produced a consistent outcome across all 30 runs.

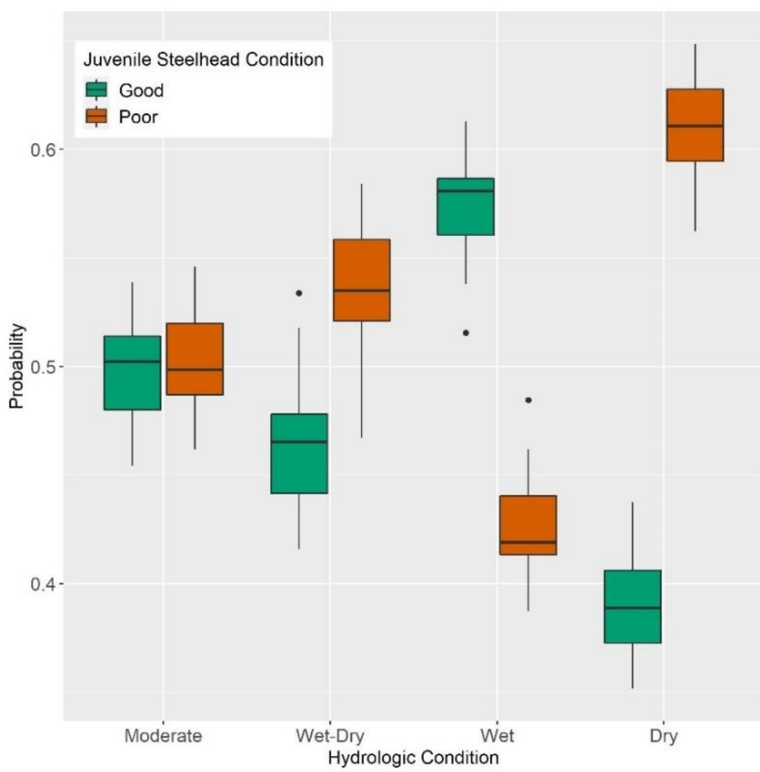


Fig. 12. The likelihood of good and poor juvenile steelhead condition using uncertainty ranges in Scenario A for Moderate, Wet – Dry, Wet, and Dry hydrologic conditions. Each box and whisker plot represents 30 model runs.

Scenario B results show that the expected probability of good juvenile steelhead condition can vary by as much as 50% depending on the hydrologic condition and the location and magnitude of uncertainties in the BN model (Fig. 13). Across all four hydrologic conditions, there was considerable variability in outcomes when the End node probabilities were changed. For example, the likelihood of good condition in a dry year is either 40% or 60% depending on whether longitudinal connectivity (E1) or food supply and fish growth (E2) are assumed most important, respectively (Fig. 13a). Under Base and Middle scenarios, juvenile steelhead condition is nearly identical in Moderate and Wet – Dry conditions. In other words, additional certainty in the middle nodes had a negligible impact on the end node under these hydrologic conditions whereas the probability of good and poor steelhead condition diverged by 40-50% under Wet and Dry conditions. There were only 8 runs that produced an absolute difference between outcomes of 40% or greater—many of which occurred when lower and middle probabilities were changed simultaneously.

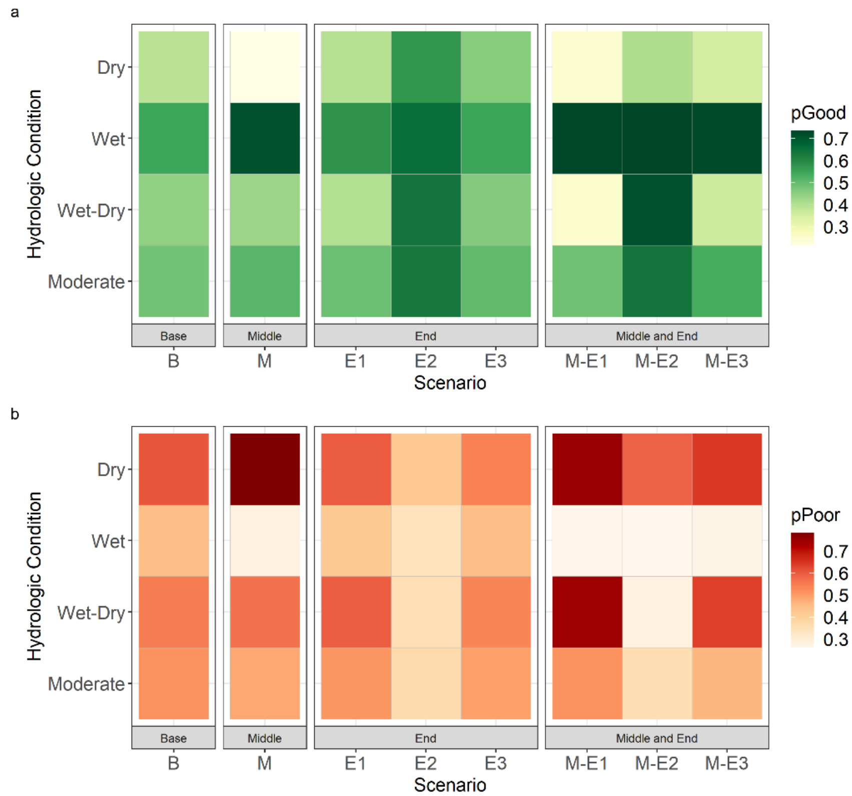


Fig. 13. The likelihood of (a) good and (b) poor juvenile steelhead condition under Scenario B runs. The Middle (M) scenario evaluates increased certainty in middle nodes, the End (E) scenario evaluates the limiting variable of longitudinal connectivity (E1), food supply and fish growth (E2), or disease (E3) to juvenile steelhead condition, and Middle and End (M-E) scenarios evaluate both increased certainty in middle nodes and changed probabilities in the end node.

DISCUSSION

Flow-ecology relationships are critical for developing and adaptively managing environmental flows (Horne et al., 2018). However, uncertainties often arise because ecosystems are inherently complex and are comprised of multiple interacting relationships—many of which are difficult to quantify (Acreman et al., 2014; Colloff et al., 2018; L. Poff, 2018; Williams et al., 2019). Using the well-studied and at-risk SFER watershed in northern California as a case of study, I explored uncertainty and attributes of flow-ecology relationships and found several gaps related to the temporal and spatial distribution of data used in studies, as well as the variables included within studies. I combined scenario analysis with BN modeling to represent the different levels of uncertainty present within relationships.

Attributes and Data Gaps

Results from the systematic literature review highlight regional data gaps in flow-ecology studies pertaining to the SFER watershed. Of the 66 articles reviewed, none provided an explicit and direct link to the flow regime impacting physical conditions. Rather, all flow relationships described direct relationships between flow and one of four species—algae, FYLF, steelhead, and aquatic macroinvertebrates. Colloff et al. (2018) drew a similar conclusion when they reviewed 359 datasets and found that only 9% were useful for testing flow-ecology predictions—highlighting challenges of relying on data collected for other purposes to gain insight on flow-ecology relationships. The scarcity of flow – physical condition relationships highlights a serious gap in peer-reviewed literature, especially given the growing interest in understanding how flow and other environmental factors affect species (Poff, 2018). Although flow is implicit in many physical condition relationships, water managers ideally require thresholds and defensible evidence for management purposes (Acreman, 2005; Colloff et al., 2018; Miller et al., 2018).

Although the flow regime was often discussed as a site characteristic or mentioned broadly in discussion, few studies provided explicit and quantifiable ecological responses to streamflow or specific ecological flow targets. The most well described seasonal flow components were peak flows and the spring recession, which were often related to algae blooms and FYLF, respectively. Flow was most often discussed in terms of magnitude and no relationships discussed flow in terms of duration or frequency. These results are similar to a literature review of low-flow studies conducted by Walters (2016) who found that 65% of authors characterized low flow in terms of magnitude only.

The dearth of flow-specific relationships in peer-reviewed studies is particularly problematic for some environmental flow methods, such as the functional flows approach, which focus on maintaining key aspects of the natural flow regime understood to support a suite of ecological and geomorphic functions (e.g., peak flows, spring recession) (Escobar-Arias & Pasternack, 2010; Yarnell et al., 2015, 2020). My results suggest that relationships between specific aspects of the flow regime and species responses are not widely available in SFER peer-reviewed literature but may be available for certain species (e.g., algae, FYLF) at well-studied locations. Flow-specific relationships have been developed at larger scales using different approaches, such as the Ecological Limits of Hydrologic Alteration framework (Poff et al., 2010); however, these relationships are characterized by flow alteration and are mainly available for macroinvertebrates or other intensively monitored species (Buchanan et al., 2013; Solans & García de Jalón, 2016; Stein et al., 2017). Flow-specific relationships pertaining specifically to the SFER watershed and encompassing ecological response to the natural flow regime may be more readily available in the grey literature or may require targeted field monitoring to identify flow thresholds.

The limited availability of flow-ecology relationships across species (Fig. 5) highlights challenges for implementing or evaluating environmental flows at an ecosystem level, which is increasingly required by holistic approaches (Horne et al., 2017). Sixteen species groups were included in relationships but four species groups—aquatic macroinvertebrates, algae, steelhead, and FYLF—made up nearly 70% of species within relationships. Although juvenile steelhead were well represented across relationships, they were often present in food web ecology studies (e.g., algal response to steelhead and roach exclusion, Power, 1990) where they were not the main focus. These gaps create challenges for understanding flow, food, and habitat requirements for species of management interest, including juvenile steelhead. Further, no relationships were available within SFER peer-reviewed literature for coho and chinook salmon despite their federally threatened status in the watershed (California Department of Fish and Wildlife, 2014).

Effects of Spatial and Hydrologic Variability

Results from the literature review emphasize the challenges of scaling flow-ecology relationships through space and time, which is an ongoing focus for scientists and water managers (Chen & Olden, 2018; Horne et al., 2019; Poff, 2018). Data collection preferentially occurred in the dry summer months (Fig. 6). This may be a result of field accessibility issues during the wet season or targeted interest in the biotic and abiotic interactions that characterize Mediterranean ecosystems during the dry season (Gasith & Resh, 1999). These results confirm the need to expand sampling beyond summer months, especially for juvenile steelhead (Tattam et al., 2017). Further, the fact that 65% of flow-ecology relationships were developed using data that only spanned one WYT reveals that most flow-ecology studies only capture a snapshot of the highly variable Mediterranean hydrologic regime and do not consider the effects of seasonal or interannual variability. This presents a tradeoff whereby a relationship developed across consecutive dry years, for example, may be more uniform compared to a relationship developed across different WYTs; however, these relationships would fail to characterize interannual variability (Lynch et al., 2018). This is important given that environmental flows often vary by WYT (Null & Viers, 2013; Rheinheimer et al., 2016).

While hydrologic variability is a defining feature of Mediterranean ecosystems (Cid et al., 2017; Gasith & Resh, 1999), it appears to influence some flow-ecology relationships more than others. For example, the timing of oviposition for FYLF occurred earlier and for a shorter duration during dry years and occurred later and for a longer duration in wet years (Kupferberg, 1996). In addition, WYT affects upstream adult steelhead migration, but the exact effect differed by location as it interacted with geomorphic features (Kelson, et al., 2020). In contrast, WYT did not influence the timing of juvenile steelhead outmigration or growth rate over the summer (Kelson & Carlson, 2019). Additional research is needed to determine which relationships are more sensitive to local controls, such as WYT or channel setting, and which can be more readily extrapolated.

Watershed characteristics (e.g., channel type, geology) vary spatially across the SFER watershed, creating a gradient of environmental conditions. My results show that most peer-reviewed relationships for the SFER are being developed using data collected in relatively pristine environments and in a limited number of geomorphic settings (Figures 8, 9). These results emphasize concerns of biological data being collected from a small subset of streams (George et al., 2021; Poff & Zimmerman, 2010) and spatial autocorrelation in data collection (Bruckerhoff, Leasure, & Magoulick, 2019) that is then used to inform water management over much larger spatial scales. These spatial data constraints limit our ability to understand and quantify how flow-ecology relationships vary across environmental gradients (Acreman et al., 2014).

The extent to which flow-ecology relationships can be extrapolated may also differ across watersheds with similar flow regimes (Chen & Olden, 2018) or across different flow regimes (Bruckerhoff et al., 2019). Although the majority of the SFER watershed falls within a winter rain storm dominated flow regime, flow regimes in surrounding north coast streams include rain and seasonal groundwater, perennial groundwater and rain, low- and high-volume snowmelt and rain, and groundwater (Lane et al., 2017). Thus, it is unlikely that flow-ecology relationships developed in the SFER watershed—a winter storms dominated flow regime—can be directly extrapolated to neighboring snowmelt dominated areas like the Sierra Nevadas, since species in Mediterranean regions are highly adapted to local flow regime disturbances (Gasith & Resh, 1999). Lithology also plays an important role in northern California. For example, the SFER watershed consists of a thick Coastal Belt lithology while the mainstem Eel River is underlain by a thin Central Belt lithology (Dralle et al., 2018; Hahm et al., 2019). Although the climate is similar between the neighboring systems (primarily winter storms), the dominant runoff mechanisms and resulting streamflow, sediment and temperature regimes will differ depending on the underlying lithology, which may impact ecological responses. Understanding the spatial attributes of flow-ecology relationships can improve the ability to accurately interpret and extrapolate the relationships to other areas (Bruckerhoff et al., 2019).

The SFER and surrounding watersheds support a diverse range of native aquatic species, such as several salmonids that are endemic to northern California (Moyle et al., 2017), which may limit the applicability of flow-ecology relationships broadly across other Mediterranean regions. Similarly, the Mediterranean Basin supports a variety of endemic freshwater biota (Tierno de Figueroa et al., 2013) that are adapted to two annual flow peaks compared to the single peak that occurs during California winters (Bonada & Resh, 2013). Thus, while Mediterranean species all poses similar life history strategies (Gasith & Resh, 1999), individual species are highly specific to each region and are adapted to different flow regimes. Therefore, flow-ecology relationships developed in the SFER watershed may be more reasonably extrapolated to a similar species and area (e.g., steelhead in an Oregon stream) than broadly to other Mediterranean regions. However, the methods proposed here to critically assess the spatial and temporal coverage of existing studies and incorporate uncertainty levels into BN modeling through scenario analysis are readily applicable to other regions.

Representing Uncertainty Using Scenario Analysis

Despite uncertain conditions and incomplete knowledge, natural resource managers are tasked with making decisions to support aquatic ecosystems and require tools to do so (Acreman, 2005; Pullin et al., 2004). Similar to other BN studies (e.g., Chan et al., 2012; Stewart-Koster et al., 2010), my model was developed by creating the model structure and assigning node states and probabilities based on the literature and personal judgement. However, unlike most studies that inherently apply Level 2 uncertainty, I used scenario analysis to explore several sets of possible probabilities for flow-ecology relationships. The scenario analysis enabled more extensive consideration of Level 3 uncertainty in ecological systems to reflect the inherent complexity within ecosystems (Acreman et al., 2014; Colloff et al., 2018; L. Poff, 2018; Williams et al., 2019). This research thus bridges the gap between more fully representing uncertainty while still using established and accessible tools like BN models.

Results from Scenario A (Fig. 12) show that even small uncertainties in the BN model base probabilities may substantially alter the ecological response in some hydrologic conditions. Under Level 3 uncertainty, the BN model produces a consistent ecological response under Wet and Dry conditions, which represent hydrologic extremes in this region. These results imply that under Wet and Dry conditions, the BN model and subsequent relationships may be more readily applied to other locations with similar characteristics (e.g., Mediterranean climate, similar species composition), especially if scenario analysis is used to understand the potential outcome space given uncertainty in the probabilities. By contrast, model outcomes were less consistent for more Moderate hydrologic conditions, implying that Level 3 uncertainties are more significant during moderate hydrologic years. This presents a challenge for understanding flow-ecology relationships in the context of interannual variability and understanding the effects of water management decisions in moderate hydrologic years. However, based on the anticipated increase in precipitation and drought extremes in northern California (Swain et al., 2018), it is likely that hydrologic extremes will be an ongoing focus of water and habitat management.

The location and magnitude of uncertainties in the BN model influenced the expected ecological outcome. Near perfect certainty in the middle node relationships (e.g., algae to food supply) improved certainty in the ecological outcome under Wet and Dry hydrologic conditions but had no impact under Moderate or Wet – Dry conditions (Fig. 13). Under Dry conditions, the likelihood of good steelhead condition decreased from 39% to 22% when the base probabilities were altered to represent more certainty in relationships. Under Moderate conditions, the likelihood of good condition only differed by 3% compared to the outcome under base probabilities. It is unlikely that the level of certainty displayed in this scenario would ever be achieved in real-world flow-ecology relationships; however, probabilities like these are often used for modeling and management purposes. For example, Shenton et al. (2011) specify probabilities for triggering Grayling spawning as 0% (triggered) and 100% (not triggered) for several combinations of pre spawning condition, late fall water temperature, and fall pulse frequency and volume. Horne et al. (2018) characterize the state of two nodes (macroinvertebrate biomass and diversity and existing overall condition for grayling) as 100% "good condition." Given the uncertainties highlighted in this and other research efforts, as well as imperfect sampling detection of aquatic species (Gwinn et al., 2016), it seems unreasonable to characterize ecological condition as 100%— even for modeling purposes. By doing so, BN models may overrepresent certainty in a particular ecological outcome and give managers false confidence. My results show that this bias may be magnified under certain hydrologic conditions—such as Dry years—which are challenging for water managers because competition for water exists among users and the environment (Gasith & Resh, 1999).

Scenario B results emphasize that uncertainty in our understanding of limiting variables has a large impact on the expected ecological outcome. Under the same hydrologic conditions, steelhead condition could shift towards good or poor depending on whether food supply and fish growth or longitudinal connectivity were assumed to be most important for steelhead, respectively. The importance of these additional factors may also change through time or by location. For example, disease may become more prevalent across the watershed as stream reaches warm (Schaaf et al., 2017) and additional environmental stressors, such as non-native predation, may become more important as invasive species expand throughout the Eel River basin (Moyle et al., 2017). Given challenges in isolating limiting factors that impact aquatic species (Holmes et al., 2018) and knowing how relationships will hold through time (Horne et al., 2019), traditional BN modeling using only one set of assumptions runs the risk of making incorrect assumptions and drawing inaccurate conclusions about an ecological outcome.

Applications for Water Resources Management

Limited resources are available to characterize flow-ecology relationships for individual rivers (Chen & Olden, 2018; George et al., 2021), so methods are needed to prioritize data collection efforts and facilitate effective extrapolation of existing flow-ecology relationships across a watershed or to other systems. My results elucidated several gaps in flow-ecology relationships that can explicitly inform the design of field monitoring networks to support ongoing environmental flow development in the SFER watershed. Based on the body of literature reviewed, additional research efforts are needed to describe flow – physical condition relationships given that half of the existing flow-ecology studies characterize physical condition – species relationships. This could be accomplished using physically-based models such as hydrodynamic and stream temperature models, or through empirical relationships based on available or additional monitoring data. Applying my literature review process to existing data and grey literature would help link existing information sources within the watershed and prevent data collection overlap. Given that most flow-ecology relationships are developed using data collected over summer low flow months (Fig. 6b), I also recommend that state agencies, academic research institutions, and related partners continue to support long-term data collection efforts across multiple seasons. These efforts will help characterize ecological responses during winter high flows, which are needed to set wet season diversion limits for cannabis growers in the region and appropriately size off-stream storage tanks (State Water Resources Control Board, 2019). Long-term data collection is especially pressing given that northern California is one of only three ecohydraulic regions in the U.S. to not possess significant regional flow-ecology relationships due to on a lack of adequate fish richness and reach-scale data (George et al., 2021). Finally, my results show that clustered data collection efforts in the SFER watershed have limited the distribution of relationships to only a few geomorphic channel types (Fig. 9). In addition to continuing data collection at established sites, additional monitoring sites are needed for confined high-gradient cobble-boulder step-pool/cascade streams (SFE07), which are underrepresented across relationships relative to their occurrence in the watershed, and partly-confined gravel-cobble, uniform streams (SFE05), which comprise nearly 60% of the SFER stream network but are represented mostly through data collected within the Angelo research reserve.

A major challenge for water managers is contextualizing the impact of flow with other limiting factors for ecosystems such as physical habitat or food web dynamics, which may or may not be impacted by flow (Poff, 2018). A benefit of BN models is their ability to highlight additional relevant factors to an ecological outcome alongside flow, such as land use and habitat conditions. However, due to limited data availability, elicitation of relationships and probabilities are often subject to expert opinion—which is inevitably uncertain (Cook, 1991). Using an exploratory model pertaining to the SFER watershed, I have demonstrated an approach for combining Level 2 and 3 uncertainty within BN models, which removes the need to try to specify a single ‘accurate’ probability for relationships. Water managers can apply the scenarios developed in this research (e.g., uncertainty ranges in base probabilities) to existing BN models or develop new scenarios to explore other Level 3 uncertainties. For example, the SFER technical advisory committee—a group of scientists and researchers in the watershed working to develop environmental flows—could use scenario analysis to represent Level 3 model structure uncertainty by testing the ecological outcome response based on different conceptual models other than the structure proposed here. Water managers could also develop scenarios to represent the impact of different management actions on an ecological outcome, such as setting diversion limits, forest and road management, and habitat improvement projects.

Limitations and Future Research

Because of the complexity, variability, and number of flow-ecology studies considered in this study, several simplifications were made. Since studies often used data collected throughout the SFER watershed, WYT was calculated for the entire watershed using streamflow data from Elder Creek, a relatively pristine catchment with a long gauge record. Uncertainty associated with this decision is expected to be minimal given that climate conditions are relatively uniform across the study watershed. The WYT analysis also only considered whether a given WYT was represented in a flow-ecology relationship and not the number (e.g., 3 dry years) or sequence (e.g., dry-wet-dry) of WYTs. Based on the importance of antecedent conditions in environmental water management (Horne et al., 2018), this is a critical area for future research. For example, does a dry year following a wet year lead to different ecological outcomes than a dry year following a dry year? Assumptions were also made related to study locations. Since the aim was to characterize the distribution of flow-ecology data across channel types, I assigned individual data collection locations to the nearest stream segment, which was often estimated based on vague spatial descriptions in the studies. Finally, insights gained through this study are drawn from the peer-reviewed literature through a rigorous review process. Expanding the study methodology to include other information sources outside the scope of this project, such as state agency monitoring data or grey literature (e.g., Asarian, Higgins, & Trichilo, 2016; Higgins, 2013), would inevitably lead to additional data, flow-ecology relationships, and insights, particularly given the importance of these data sources to managers and their abundance in the SFER watershed. Since the scope of this research was limited to peer-reviewed studies developed for the SFER watershed, no studies developed outside the watershed or general flume and laboratory experiments were considered. This research could also be extended by applying other review methodologies to assess the data availability and reproducibility of studies (Stagge et al., 2019) or the quality of support for general flow-ecology hypotheses (Norris et al., 2012).

The main purpose of the exploratory BN modeling in this study was to exemplify how information extracted through a rigorous review of the peer-reviewed literature can be compiled into a BN model and how various levels of uncertainty can be explicitly represented. As a result, the model does not represent the full range of conditions important to juvenile steelhead and does not consider other ecological outcomes, including other steelhead life stages (e.g., migrating juveniles, spawning adults). Similarly, the conceptual model, BN model, and conditional probabilities reflect my own judgment—which is inherently uncertain (Cook, 1991)—and do not reflect insights from experts or relationships derived from other information and data sources. Including these outside information sources would help refine the model structure and probabilities, which will likely improve representation of ecological outcomes. The scenario analysis framework described here can be applied to existing or future BN models in the SFER and other watersheds to provide insights under multiple levels of uncertainties and in light of additional information.

CONCLUSION

A conceptual and quantitative understanding of flow-ecology relationships is critical for developing, implementing, and adaptively managing environmental flow regimes. Based on the widespread need to establish environmental flows over large areas and limited ecological data, flow-ecology relationships are often extrapolated within or outside of the area and conditions under which they are developed. Thus, it is important to examine the specific attributes of these relationships to understand potential gaps that may affect how well they apply to other areas and use modeling tools that adequately represent uncertainty in relationships.

In this study, I used the SFER watershed in northern California to explore attributes and uncertainty in flow-ecology relationships through a systematic review of peer-reviewed studies and BN modeling and scenario analysis. I found that most peer-reviewed studies in the SFER watershed encompass physical condition – species and species – species relationships while few studies contain relationships related directly to flow. In addition, data collection for relationships was spatially and temporally clustered, with over 65% of relationships developed using data from one unique WYT or channel type. An exploratory BN model and scenario analysis allowed consideration of how different levels of uncertainty in flow-ecology relationships—represented as different sets of probabilities—affect juvenile steelhead condition. I found that the location and magnitude of uncertainties in the BN model have a large impact on the modeled ecological outcome. These results, along with the inherent complexities of aquatic ecosystems, highlight the importance of accounting for realistic levels of uncertainty when applying BN models to natural systems.

My results elucidated several gaps in flow-ecology relationships that can explicitly inform the design of field monitoring networks to support ongoing environmental flow development in the SFER watershed. Recommendations include to expand field data collection efforts to the wet season and across more channel types and WYTs to generate more robust flow-ecology relationships. The results from my BN model and scenario analysis show that modeled juvenile steelhead condition was inconsistent under Moderate hydrologic conditions, which highlights the challenges of understanding the impact of water management decisions in non-extreme years and under Level 3 uncertainties. Beyond the exploratory model, this study presents a general scenario analysis approach for combining Level 2 and 3 uncertainties within a BN model. The approaches used in this study can be applied to other regions and information types to improve the understanding of flow-ecology attributes and representation of uncertainties.

DATA AVAILABILITY

The data and code to reproduce the results in this study are compiled in a Hydroshare resource and can be accessed at:

https://www.hydroshare.org/resource/a731d9971eb44518898ea21e163544be/

Haley Canham (Utah State University) downloaded all data and code and reproduced the results in the figures of this study.

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APPENDICIES

APPENDIX A. LITERATURE REVIEW PROTOCOL AND CODE DEFINITIONS

Literature Review Protocol

Articles will be read in alphabetical order according to author last name. Refer to Table A1 as you are filling out the excel file for a complete list of attribute definitions.

1. **Fill in metadata attributes**
   1.1. Enter the *title*, *year*, *journal*, and *full citation* for the article.
   1.2. Enter the *Reference* as FirstAuthorLastNameEtAlYear or LastNameYear. Create a folder in documents>SF Eel>Eco_lit_review>GIS_files with the same reference label.
   1.3. Assign a *Study_ID*. This will remain consistent for each entry of the study.
   1.4. Assign a *Unique_ID* (e.g., 1, 2, 3) for different entries. Multiple entries may be required for an individual study if:
   - There are multiple relationships for a single location (e.g., a relationship between temperature-FYLF and temperature-Steelhead at a single location)
   - There are different relationships for different locations (e.g., a different relationship between temperature-breeding on the mainstem SFER and Elder Creek). **Note:** If a single relationship is developed from data at multiple locations (e.g., throughout the watershed), use a single entry.
   - There are different relationships for different years (e.g., a different relationship between temperature-breeding for 2008 versus 2010)

2. **Read/ skim the article**
   2.1. Skim the document to get a sense of spatial and temporal attributes, including study location, date range of data used in the study, and whether these attributes vary over the results presented in the study.
   2.2. Get a sense of the type of relationship(s) and variables described in the study: Are multiple entries needed?

3. **Update metadata attributes and categorical relationship attributes**
   3.1. Add however many *unique_ID*s are required for the study (e.g., if you found 3 unique relationships, there should be 3 unique_IDs).
   3.2. For each Unique_ID, update the following categorical attributes in excel and code in atlas. These should be the same (for example species in excel is algae, species in atlas is algae). Apply atlas codes to the titles of each document. More than one codes from individual code groups may be applied. A new set of codes should be applied for each Unique_ID, even if codes are similar.
   - Category of relationship: *Relationship_category*, *Relationship*
   - Species considered in study: *Species*, *Species*
   - Flow component considered in study: *Flow_regime*, *flow*
   - Physical condition considered in study: *Physical_condition*, *physical condition*
   - Lifestage considered in study: *Lifestage_interaction*, *Lifestage/interaction*

4. **Fill in temporal attributes for each unique_ID**
   4.1. Fill in the *start and end dates* of data collected for each relationship (month/day/year)

4.2. Fill in the *start and end months* (numeric) of data collected for each relationship (month, e.g., 9 for September)
4.3. Enter the nearest, and most predominant (e.g., likely represents the majority of data), *USGS stream gage used in the study*.

5. Fill in the spatial attributes for each unique_ID

5.1. Denote the *Stream_reach* by listing the names of creeks, streams, and rivers used in the study (separated by commas).
5.2. After determining the study locations in ArcPro, go to the “Location” sheet and enter the COMID from the stream reaches where data collection occurred (under *GIS COMID* column) and the associated channel type (under *Channel Type* column). There should be a new line entry for each segment. Enter the Unique_ID and Study_ID (same as Attributes sheet) for all segment entries.

6. Denote the findings and methods of each relationship

6.1. Enter specific details about the study that are not disclosed in the spatial, temporal, or categorical attributes. These include:
- *Variables:* Specific variables within the above categories (e.g., if categorical attributes are peak flow and species, individual variables may be bankfull flow, cladophora, caddisfly)
- *Method description:* Provide a brief description of methods for each unique_ID

6.2. Provide a short *description of the findings*, including numeric values of importance. Only include the most important and easy to understand finding (e.g., can be easily understood and used by managers).
6.3. For each relationship, note whether it’s *qualitative or quantitative* and provide the *units* of variables in the relationship. Note any *thresholds* derived from the relationship or referenced in the study (e.g., high flow > 500 cfs)

7. Update metadata

7.1. Make sure all metadata (e.g., title, citation, reference, etc.) are filled in for each unique_ID entry.

Table A1. Attribute descriptions for SFER literature review

Attribute	Description
Unique_ID	A unique number to denote different entries in excel. Each line in the excel database needs a unique_ID (e.g., multiple unique_IDs are needed if a study has multiple relationships).
Study_ID	A unique number to denote different studies in excel. Each study in the excel database needs a unique study_ID. A single study may have multiple unique_IDs, but will only have one study_ID.
GIS COMID	A unique GIS specifier to distinguish stream segments in ArcGIS pro
Channel Type	The channel type of stream segments where data collection occurred (found through the channel type shapefile).
Reference	Use a consistent in-text citation format as a reference shorthand: Multiple authors: FirstAuthorLastNameEtAlDate (e.g., SuttleEtAl2011), Single author: LastNameDate (e.g., Power2003)
Start_date	Start date of data used in study. Enter in the format: mo-d-yr.
End_date	End date of data used in study. Enter in the format: mo-d-yr.
Month_start	Use to denote seasonality if data collection occurs across multiple years. Enter month in shorthand: Jan, Feb, Mar, etc,
Month_end	Use to denote seasonality if data collection occurs across multiple years. Enter month in shorthand: Jan, Feb, Mar, etc,
Nearest_USGS	Enter the name (e.g., Elder) of the nearest USGS gage where data collection occurred
Stream_Reach	Enter the name(s) of the river or stream where data collection occurred.
Relationship_category	Categorize the relationship as: Flow – species, Flow – physical condition, Physical condition – physical condition, species – species, Physical condition – species, or Species-physical condition. **Code in Atlas.**
Flow_Regime	Categorize the flow regime according to "flow" codes in Atlas. **Code in Atlas.** Make a new code if needed.
Species	Categorize the species according to "species" codes in Atlas. **Code in Atlas.** Make a new code if needed.
Lifestage_interaction	Categorize lifestage according to "lifestage,interaction" codes in Atlas. Entries should be separated by a comma (e.g., juvenile, rearing). **Code in Atlas.** Make a new code if needed.
Physical_condition	Categorize the physical condition according to "physical condition" code in Atlas. **Code in Atlas.** Make a new code if needed.
Method_Description	Brief description of methods used (e.g., took water samples at 5 transects on Elder Creek, measured algae concentrations at 3 point locations, analyzed with ANOVA)
Variables	Provide additional specifics of flow regime, species, and physical condition categories (e.g., bankfull flow, cladophora)
Relationship_description	Brief summary (few sentences) of the relationship, including numeric descriptors.
Quant_Qual	Categorize as "Qualitative" or "Quantitative"
Type_of_Relationship	Brief overview of relationship (e.g., probabilistic outcome from field data)

Units	Provide the units used to measure variables (e.g., cfs, cm)
Threshold/States	Provide thresholds and associated values if provided within study (e.g., high temperature > 24C)
Uncertainty	Rate as 1, 2, 3, or 4 (low to high)
Title	Full title of the study
Journal	Title of Journal where article is published
Year	Year published
Citation	Full citation (APA)
Notes	Miscellaneous notes

Atlas Code Definitions

Table A2. Definition for categorical attribute codes applied in Atlas

Code Group	Code	Definition
Flow	Dry-season baseflow	Relationship related to summer baseflow (e.g., summer low flow, dry-season baseflow) or any reference to flow during the months of June–October. This code must be used with a flow relationship code (flow – physical condition, flow – species). If possible, use this code with a flow specifier (timing, magnitude, duration, rate of change, frequency).
Flow	Duration	Flow specifier related to the duration (e.g., 4 weeks, 4 months) of individual flow events or seasonal functional flows within a flow relationship. Must be used with a flow code (e.g., dry-season baseflow).
Flow	Frequency	Flow specifier related to the frequency (e.g., every 5 years, at least once a year) of individual flow events or seasonal functional flows within a flow relationship. Must be used with a flow code (e.g., dry-season baseflow).
Flow	Magnitude	Flow specifier related to the magnitude (e.g., 50 cfs) of individual flow events or seasonal functional flows within a flow relationship. Must be used with a flow code (e.g., dry-season baseflow).
Flow	Peak flow	Relationship related to peak flows (e.g., high winter flows, winter storms, bankfull) or any reference to flow during the months of Nov–March. This code must be used with a flow relationship code (flow – physical condition, flow – species). If possible, use this code with a flow specifier (timing, magnitude, duration, rate of change, frequency).
Flow	Rate of change	Flow specifier related to the rate of change (e.g., 200 cfs over 5 days) of individual flow events or seasonal functional flows within a flow relationship. Must be used with a flow code (e.g., dry-season baseflow).

Flow	Spring recession	Relationship related to spring recession flows (e.g., spring spates, receding flows, spring flows) or any reference to flow during the months of April–June. This code must be used with a flow relationship code (flow – physical condition, flow – species). If possible, use this code with a flow specifier (timing, magnitude, duration, rate of change, frequency).
Flow	Timing	Flow specifier related to the timing (e.g., early January–Feb) of individual flow events or seasonal functional flows within a flow relationship. Must be used with a flow code (e.g., dry-season baseflow).
Flow	Wet-season initiation	Relationship related to wet-season initiation flows (e.g., fall flush, first high flows) or any reference to flow during the months of Nov–Dec. This code must be used with a flow relationship code (flow – physical condition, flow – species). If possible, use this code with a flow specifier (timing, magnitude, duration, rate of change, frequency).
Flow	Winter-baseflow	Relationship related to winter baseflows or any reference to non-storm flows during Dec–Mar. This code must be used with a flow relationship code (flow – physical condition, flow – species). If possible, use this code with a flow specifier (timing, magnitude, duration, rate of change, frequency).
Flow	WYT	Relationship related to the water year type of the entire flow regime. This code must be used with a flow relationship code (flow – physical condition, flow – species). If possible, use this code with a flow specifier (timing, magnitude, duration, rate of change, frequency).
Identity	Keep	Use as a sorting code to designate article for the SFER flow-ecology literature review
Identity	Reject	Use for articles that are not relevant for the SFER flow-ecology literature review. Non-relevant articles include those that do not relate to instream processes including aquatic species, physical conditions, or flow. Articles may also be rejected if they do not collect any original data within the SFER watershed (but reference studies that do) or reference processes beyond the basic understanding of flow-ecology relationships (e.g., carbon flow in food webs).
Identity	uncertain	To be used for articles that may be relevant for the literature review, but the coder is uncertain.
Life stage/ interaction	Adult	To be used as an adult life stage specifier for aquatic species. Always use with a species code (e.g., steelhead) and a species relationship code (species – species, flow – species, physical condition – species). If possible, use with an interaction specifier (e.g., Breeding, predation).

Life stage/ interaction	Breeding	To be used as an interaction specifier for breeding or reproduction of aquatic species. Always use with a species code (e.g., steelhead) and a species relationship code (species – species, flow – species, physical condition – species). If possible, use with a life stage specifier (e.g., adult, juvenile).
Life stage/ interaction	Feeding	To be used as an interaction specifier for feeding interactions between aquatic species. Use with any mention of dietary preferences, feeding patterns, or general food web ecology. Always use with a species code (e.g., steelhead) and a species relationship code (species – species, flow – species, physical condition – species). If possible, use with a life stage specifier (e.g., adult, juvenile).
Life stage/ interaction	Invasive predation	To be used as an interaction specifier for predation between non-native and native aquatic species. Always use with a species code (e.g., steelhead) and a species relationship code (species – species, flow – species, physical condition – species). If possible, use with a life stage specifier (e.g., adult, juvenile).
Life stage/ interaction	Juvenile	To be used as a juvenile life stage specifier for aquatic species. Applies to any reference of juvenile aquatic species, such as a tadpole, fry, etc. Always use with a species code (e.g., steelhead) and a species relationship code (species – species, flow – species, physical condition – species). If possible, use with an interaction specifier (e.g., Breeding, predation).
Life stage/ interaction	Migration	To be used as an interaction specifier for migrating aquatic species. Always use with a species code (e.g., steelhead) and a species relationship code (species – species, flow – species, physical condition – species). If possible, use with a life stage specifier (e.g., adult, juvenile).
Life stage/ interaction	Rearing	To be used as an interaction specifier for rearing aquatic species. Always use with a species code (e.g., Steelhead) and a species relationship code (species – species, flow – species, physical condition – species). If possible, use with a life stage specifier (e.g., adult, juvenile).
Life stage/ interaction	Seed	To be used as a seed life stage specifier for aquatic or riparian vegetation. Always use with a species code (e.g., vegetation) and a species relationship code (species – species, flow – species, physical condition – species).
Life stage/ interaction	Seedling	To be used as a seedling life stage specifier for aquatic or riparian vegetation (e.g., young plant). Always use with a species code (e.g., vegetation) and a species relationship code (species – species, flow – species, physical condition – species).

Physical Condition	Depth	Relationship related to the depth of water in a stream or river. This code must always be used whenever a physical condition relationship code is used (e.g., physical condition – species, physical condition – physical condition, flow – physical condition).
Physical Condition	Dimensionless	Relationship related to dimensionless parameters of physical conditions (e.g., scaling relationships). This code must always be used whenever a physical condition relationship code is used (e.g., physical condition – species, physical condition – physical condition, flow – physical condition).
Physical Condition	General habitat	Relationship related to more than 3 physical habitat conditions, such as velocity, depth, light, etc. Use this code when physical habitat assessments are performed for a species and include multiple physical conditions. This code must always be used whenever a physical condition relationship code is used (e.g., physical condition – species, physical condition – physical condition, flow – physical condition).
Physical Condition	Geomorphic	Relationship related to geomorphic features that are specific to a certain channel type (e.g., channel slope, contributing area). This code may also be used in reference to relationships that vary by location. This code must always be used whenever a physical condition relationship code is used (e.g., physical condition – species, physical condition – physical condition, flow – physical condition).
Physical Condition	Light	Relationship related to the amount of light entering a stream or river, or in reference to the amount of shade. This code must always be used whenever a physical condition relationship code is used (e.g., physical condition – species, physical condition – physical condition, flow – physical condition).
Physical Condition	Nutrients	Relationship related to instream nutrients (e.g., nitrogen, phosphorus). This code must always be used whenever a physical condition relationship code is used (e.g., physical condition – species, physical condition – physical condition, flow – physical condition).
Physical Condition	Sediment	Relationship related to instream sediment (e.g., fine sediment, boulders, sediment transport). This code must always be used whenever a physical condition relationship code is used (e.g., physical condition – species, physical condition – physical condition, flow – physical condition).
Physical Condition	Shear stress	Relationship related to shear stress experienced in streams and rivers. This code can be applied to any mention of erosion or scour. This code must always be used whenever a physical condition relationship code is used (e.g., physical condition – species, physical condition – physical condition, flow – physical condition).

Physical Condition	Temperature	Relationship related to air or water temperature. This code must always be used whenever a physical condition relationship code is used (e.g., physical condition – species, physical condition – physical condition, flow – physical condition).
Physical Condition	velocity	Relationship related to the velocity of water in streams or rivers. This code must always be used whenever a physical condition relationship code is used (e.g., physical condition – species, physical condition – physical condition, flow – physical condition).
Physical Condition	Width	Relationship related to the cross-sectional width in a stream or river. This code must always be used whenever a physical condition relationship code is used (e.g., physical condition – species, physical condition – physical condition, flow – physical condition).
Relationship	Flow – physical condition	A relationship specifier that denotes relationships of the flow regime (e.g., summer base flow, peak flow) and physical conditions (e.g., temperature, sediment). This code should always be accompanied by flow and physical conditions specifier codes.
Relationship	Flow – species	A relationship specifier that denotes relationships of the flow regime (e.g., summer base flow, peak flow) and aquatic species (e.g., steelhead, FYLF). This code should always be accompanied by flow and species specifier codes, and life stage/interaction codes if possible.
Relationship	Physical condition – physical condition	A relationship specifier that denotes relationships of physical conditions (e.g., water temperature) and other physical conditions (e.g., nutrients). This code should always be accompanied by physical condition codes.
Relationship	Physical condition – species	A relationship specifier that denotes relationships of a physical condition (e.g., water temperature) and an aquatic species (e.g., steelhead). This code should always be accompanied by physical condition and species codes, and a life stage/interaction code if possible.
Relationship	Species-physical condition	A relationship specifier that denotes a species – physical condition relationships (e.g., plant photosynthesis impacting DO). This code should always be accompanied by species (e.g., steelhead) and physical condition codes.
Relationship	Species – species	A relationship specifier that denotes species – species relationships. This code should always be accompanied by species (e.g., steelhead) and life stage/interaction codes.
Species	Algae	Relationship related to aquatic algae (e.g., Cladophora, macroalgae, epiphytes, etc.). This code must always be used whenever a species relationship code is used (e.g., physical condition – species, species – species, flow – species). If possible, use a life stage/interaction specifier code.

Species	Aquatic macro.	Relationship related to aquatic macroinvertebrates (e.g., caddisflies, midges, mayflies, etc.). This code must always be used whenever a species relationship code is used (e.g., physical condition – species, species – species, flow – species). If possible, use a life stage/interaction specifier code.
Species	Aquatic snail	Relationship related to an aquatic snail. This code must always be used whenever a species relationship code is used (e.g., physical condition – species, species – species, flow – species). If possible, use a life stage/interaction specifier code.
Species	Bull Frog	Relationship related to the invasive bullfrog. This code must always be used whenever a species relationship code is used (e.g., physical condition – species, species – species, flow – species). If possible, use a life stage/interaction specifier code.
Species	Chinook	Relationship related to Chinook salmon. This code must always be used whenever a species relationship code is used (e.g., physical condition – species, species – species, flow – species). If possible, use a life stage/interaction specifier code.
Species	Coho	Relationship related to Coho salmon. This code must always be used whenever a species relationship code is used (e.g., physical condition – species, species – species, flow – species). If possible, use a life stage/interaction specifier code.
Species	Cyanobacteria	Relationship related to the production of toxic cyanobacteria from aquatic algae. Always use with the Algae code. This code must always be used whenever a species relationship code is used (e.g., physical condition – species, species – species, flow – species). If possible, use a life stage/interaction specifier code.
Species	FYLF	Relationship related to the Foothill Yellow Legged Frog. This code must always be used whenever a species relationship code is used (e.g., physical condition – species, species – species, flow – species). If possible, use a life stage/interaction specifier code.
Species	Lamprey	Relationship related to the Pacific Lamprey. This code must always be used whenever a species relationship code is used (e.g., physical condition – species, species – species, flow – species). If possible, use a life stage/interaction specifier code.
Species	Mussel	Relationship related to aquatic mussels. This code must always be used whenever a species relationship code is used (e.g., physical condition – species, species – species, flow – species). If possible, use a life stage/interaction specifier code.

Species	Native misc. fish	Relationship related to miscellaneous native fish (i.e., Roach). This code must always be used whenever a species relationship code is used (e.g., physical condition – species, species – species, flow – species). If possible, use a life stage/interaction specifier code.
Species	Pacific tree frog	Relationship related to the Pacific Tree Frog. This code must always be used whenever a species relationship code is used (e.g., physical condition – species, species – species, flow – species). If possible, use a life stage/interaction specifier code.
Species	Pikeminnow	Relationship related to the non-native Sacramento pikeminnow. This code must always be used whenever a species relationship code is used (e.g., physical condition – species, species – species, flow – species). If possible, use a life stage/interaction specifier code.
Species	Salamander	Relationship related to native aquatic salamanders. This code must always be used whenever a species relationship code is used (e.g., physical condition – species, species – species, flow – species). If possible, use a life stage/interaction specifier code.
Species	Sculpin	Relationship related to sculpin. This code must always be used whenever a species relationship code is used (e.g., physical condition – species, species – species, flow – species). If possible, use a life stage/interaction specifier code.
Species	Steelhead	Relationship related to steelhead trout. This code must always be used whenever a species relationship code is used (e.g., physical condition – species, species – species, flow – species). If possible, use a life stage/interaction specifier code.
Species	Terrestrial Macro	Relationship related to terrestrial macroinvertebrates (e.g., grasshoppers). This code must always be used whenever a species relationship code is used (e.g., physical condition – species, species – species, flow – species). If possible, use a life stage/interaction specifier code.
Species	Vegetation	Relationship related to aquatic or riparian vegetation (e.g., Sedge, willows, Alder). This code must always be used whenever a species relationship code is used (e.g., physical condition – species, species – species, flow – species). If possible, use a life stage/interaction specifier code.

APPENDIX B. BAYESIAN NETWORK MODEL NODE STATES AND PROBABILITIES

Node States

Table B1. Bayesian network model node states

Variable	States	Metric	Source

Peak flow	Low	< bankfull Q	Taken direct from Power et al. (2008) [Unique_ID 68]
	High	≥ bankfull Q	
Algae bloom	Large	length ≥ 50 cm	Taken direct from Power et al. (2008) [Unique_ID 68]
	Small	length < 50 cm	
Fine sediment	Low	≤ 40% embeddedness	States (low, high) and ranges (%) subjectively denoted by author using empirical values in Suttle et al. (2004) as a reference [Unique_ID 75]
	High	41-100% embeddedness	
Fish growth	Low	≤ 0.14 mm/d	States (low, high) and ranges (mm/d) subjectively denoted by author using empirical values in Suttle et al. (2004) as a reference. [Unique_ID 75]
	High	≥0.15 mm/d	
Dry-season baseflow	Low	≤ 7Q10 flow	Common low flow statistic used by USGS. Annual 7-day minimum flow with a recurrence interval of 10 years
	High	> 7Q10 flow	
Temperature (ADM)	Low	<23 C	Taken direct from Schaaf et al (2017) [Unique_ID 71], who noted that 23C is a threshold for blackspot infection
	High	≥23 C	
Diseased individuals (proportion)	Low	<50%	Taken direct from Schaaf et al (2017) [Unique_ID 71], who noted reported infection in terms of "50%" infected
	High	≥50%	
Longitudinal connectivity	Low	≥ 50% pools isolated	Authors' judgement
	High	< 50% pools isolated	
Food supply	High	Vulnerable insect abundance > armored insect abundance	Conceptually based on Power et al (2008) [Unique_ID 70] and Marks et al (2000) [Unique_ID 55]
	Low	Vulnerable insect abundance < armored insect abundance	
Juvenile Steelhead condition	Good	Non-negative population growth rate	Authors' judgement
	Poor	Negative population growth rate	

Hydrologic Nodes

Table B2. Conditional probability table for the Peak Flow node, Moderate hydrologic conditions

Peak Flow		Source	Justification
Low	High	Hydrologic statistics	For any given year, the probability of reaching bankfull based on a recurrence interval of 1.5 years is 1/1.5 yrs., or 0.67 (round to 0.7). The probability of not reaching bankfull is 1- 0.7, or 0.3
0.3	0.7		

Table B3. Conditional probability table for the Dry-season Baseflow node, Moderate hydrologic conditions

Dry-season Baseflow		Source	Justification
Low	High	Hydrologic statistics	For any given year, the probability of reaching the 7-day, 2-year low flow volume is equal to 1/2 yrs., or 0.5
0.5	0.5		

Table B4. Conditional probability table for the Peak Flow node, Wet - Dry hydrologic conditions

Peak Flow		Source	Justification
Low	High	Authors' judgement	Wet-Dry conditions occur when a wet winter (peak flow ≥ bankfull flow) is followed by a dry summer (≤ 7-day, 2-year low flow volume)
0.05	0.95		

Table B5. Conditional probability table for the Dry-season Baseflow node, Wet - Dry hydrologic conditions

Dry-season Baseflow		Source	Justification
Low	High	Authors' judgement	Wet-Dry conditions occur when a wet winter (peak flow ≥ bankfull flow) is followed by a dry summer (≤ 7-day, 2-year low flow volume)
0.95	0.05		

Table B6. Conditional probability table for the Peak Flow node, Dry hydrologic conditions

Peak Flow		Source	Justification
Low	High	Authors' judgement	Dry conditions occur when a dry winter (peak flow < bankfull flow) is followed by a dry summer (≤7-day, 2-year low flow volume)
0.95	0.05		

Table B7. Conditional probability table for the Dry-season Baseflow node, Dry hydrologic conditions

Dry-season Baseflow		Source	Justification
Low	High	Authors' judgement	Dry conditions occur when a dry winter (peak flow < bankfull flow) is followed by a dry summer (≤7-day, 2-year low flow volume)
0.95	0.05		

Table B8. Conditional probability table for the Peak Flow node, Wet hydrologic conditions

Peak Flow		Source	Justification
Low	High		

0.05	0.95	Authors' judgement	Wet conditions occur when a wet winter (peak flow ≥ bankfull flow) is followed by a wet summer (>7-day, 2-year low flow volume

Table B9. Conditional probability table for the Dry-season Baseflow node, Wet hydrologic conditions

Dry-season Baseflow		Source	Justification
Low	High	Authors' judgement	Wet conditions occur when a wet winter (peak flow ≥ bankfull flow) is followed by a wet summer (>7-day, 2-year low flow volume)
0.05	0.95		

Base Conditional Probability Tables

Base Middle Nodes

Table B10. Conditional probability table (base) for the Algae Bloom node

Peak flow	**Algae Bloom**		Source	Justification
	Large	Small		
Low	0.17	0.83	Power et al. (2008)	Probabilities taken directly from a probabilistic relationship in Power et al. (2008)
High	0.75	0.25		

Table B11. Conditional probability table (base) for the Fine Sediment node

Peak flow	**Fine Sediment**		Source	Justification
	Low	High		
Low	0.4	0.6	Authors' judgement	Flows exceeding bankfull move the majority of sediment in streams
High	0.7	0.3		

Table B12. Conditional probability table (base) for the Temperature node

Dry-season baseflow	**Temperature (ADM)**		Source	Justification
	Low	High		
Low	0.3	0.7	Authors' judgement	In an open and sunlight channel like the mainstem SFER, the relationship with dry-season baseflow and temperature is likely strong
High	0.7	0.3		

Table B13. Conditional probability table (base) for the Longitudinal Connectivity node

Dry-season baseflow	**Longitudinal Connectivity**		Source	Justification
	Low	High		
Low	0.65	0.35	Authors' judgement	In the SFER, pools are known to isolate in dry years when summer baseflow is low
High	0.3	0.7		

Table B14. Conditional probability table (base) for the Diseased Individuals node

Temp. (ADM)	**Diseased Individuals (proportion)**		Source	Justification
	Low	High		
Low	0.7	0.3	Schaaf et al (2017)	Probabilities estimated from a relationship in Schaaf et al (2017), who stated that at temperatures > 23C, 50% of fish would be infected.
High	0.2	0.8		

Table B15. Conditional probability table (base) for the Fish Growth node

	Fish Growth	Source	Justification

Fine Sediment	Low	High		
Low	0.2	0.8	Suttle et al. (2004)	Probabilities estimated using a negative linear relationship between fine sediment embeddedness and fish growth.
High	0.8	0.2		

Table B16. Conditional probability table (base) for the Food Supply node

Algae Bloom	**Food Supply**		Source	Justification
	High	Low		
Large	0.6	0.4	Power et al. (2008) and Marks et al. (2000)	Probabilities estimated from observational data, which state that the trophic levels are higher in flood years as more algal energy is directed towards vulnerable taxa (e.g., mayflies, macroinvertebrate predators) instead of armored grazers.
Small	0.4	0.6		

Base End Node

Table B17. Conditional probability table (base) for the Juvenile Steelhead Condition node

Food supply	Fish growth	Long. connect.	Diseased indiv.	**Juv. Steelhead Cond.**		Source	Justification
				Good	Poor		
High	Low	Low	Low	0.5	0.5	Authors' judgement	4/4 desirable is 0.5 good, 3/4 desirable is 0.7 good, 2/4 desirable is 0.5 good, 1/4 desirable is 0.2 good, 0/4 desirable is 0.15 good. Desirable conditions include "high" food supply, "high" fish growth, "high" longitudinal connectivity, and "low" diseased individuals
High	Low	Low	High	0.2	0.8		
High	Low	High	Low	0.7	0.3		
High	Low	High	High	0.5	0.5		
High	High	Low	Low	0.7	0.3		
High	High	Low	High	0.5	0.5		
High	High	High	Low	0.8	0.2		
High	High	High	High	0.7	0.3		
Low	Low	Low	Low	0.2	0.8		
Low	Low	Low	High	0.15	0.85		
Low	Low	High	Low	0.5	0.5		
Low	Low	High	High	0.2	0.8		
Low	High	Low	Low	0.5	0.5		
Low	High	Low	High	0.2	0.8		
Low	High	High	Low	0.7	0.3		
Low	High	High	High	0.5	0.5		

Scenario A Probabilities

Middle Nodes

Table B18. Conditional probability ranges (Scenario A) for the Fine Sediment node

Peak flow	**Fine Sediment**		Probability Range	
	Low	High	Lower	Upper
Low	0.4	0.6	0.55	0.75
High	0.7	0.3	0.65	0.8

Table B19. Conditional probability ranges (Scenario A) for the Temperature node

Dry-season baseflow	**Temperature (ADM)**		Probability Range	
	Low	High	Lower	Upper
Low	0.3	0.7	0.65	0.85
High	0.7	0.3	0.6	0.8

Table B20. Conditional probability ranges (Scenario A) for the Longitudinal Connectivity node

Dry-season baseflow	**Longitudinal Connectivity**		Probability Range	
	Low	High	Lower	Upper
Low	0.65	0.35	0.6	0.8
High	0.3	0.7	0.6	0.75

Table B21. Conditional probability ranges (Scenario A) for the Diseased Individuals node

Temperature (ADM)	**Diseased Individuals (proportion)**		Probability Range	
	Low	High	Lower	Upper
Low	0.7	0.3	0.7	0.85
High	0.2	0.8	0.7	0.85

Table B22. Conditional probability ranges (Scenario A) for the Fish Growth node

Fine Sediment	**Fish Growth**		Probability Range	
	Low	High	Lower	Upper
Low	0.2	0.8	0.65	0.8
High	0.8	0.2	0.7	0.85

Table B23. Conditional probability ranges (Scenario A) for the Food Supply node

Algae Bloom	**Food Supply**		Probability Range	
	High	Low	Lower	Upper
Large	0.6	0.4	0.6	0.8
Small	0.4	0.6	0.55	0.75

End Node

Table B24. Conditional probability ranges (Scenario A) for the Juvenile Steelhead Condition node

Food supply	Fish growth	Long. connectivity	Diseased individuals	**Juvenile Steelhead Condition**		Probability Range	
				Good	Poor	Lower	Upper
High	Low	Low	Low	0.5	0.5	0.4	0.65
High	Low	Low	High	0.2	0.8	0.15	0.3
High	Low	High	Low	0.7	0.3	0.6	0.8
High	Low	High	High	0.5	0.5	0.4	0.65
High	High	Low	Low	0.7	0.3	0.65	0.8
High	High	Low	High	0.5	0.5	0.4	0.65
High	High	High	Low	0.8	0.2	0.7	0.85
High	High	High	High	0.7	0.3	0.65	0.8
Low	Low	Low	Low	0.2	0.8	0.15	0.3
Low	Low	Low	High	0.15	0.85	0.1	0.2
Low	Low	High	Low	0.5	0.5	0.4	0.65
Low	Low	High	High	0.2	0.8	0.15	0.3
Low	High	Low	Low	0.5	0.5	0.4	0.65
Low	High	Low	High	0.2	0.8	0.15	0.3
Low	High	High	Low	0.7	0.3	0.65	0.8
Low	High	High	High	0.5	0.5	0.4	0.65

Scenario A run in R.

Table B25. Scenario A probability combinations

Run #	Hydrologic Nodes	Middle Nodes		End Node
		Level 2 uncertainty	Level 3 uncertainty	
1	Moderate	Base	A1	A1
2	Moderate	Base	A2	A2
3	Moderate	Base	A3	A3
…	…	…	…	
29	Moderate	Base	A29	A29
30	Moderate	Base	A30	A30
31	Wet-Dry	Base	A1	A1
32	Wet-Dry	Base	A2	A2
33	Wet-Dry	Base	A3	A3
…	…	…	…	
59	Wet-Dry	Base	A29	A29
60	Wet-Dry	Base	A30	A30
61	Dry	Base	A1	A1
62	Dry	Base	A2	A2
63	Dry	Base	A3	A3
…	…	…	…	…
89	Dry	Base	A29	A29
90	Dry	Base	A30	A30
91	Wet	Base	A1	A1
92	Wet	Base	A2	A2
93	Wet	Base	A3	A3
…	…	…	…	…
119	Wet	Base	A29	A29
120	Wet	Base	A30	A30

Scenario B Probabilities

Middle Nodes: Increased Certainty

Table B26. Conditional probability table (Scenario B, Middle) for the Fine Sediment node

Peak flow	**Fine Sediment**	
	Low	High
Low	0.05	0.95
High	0.95	0.05

Table B27. Conditional probability table (Scenario B, Middle) for the Temperature node

Dry-season baseflow	**Temperature (ADM)**	
	Low	High
Low	0.05	0.95
High	0.95	0.05

Table B28. Conditional probability table (Scenario B, Middle) for the Longitudinal Connectivity node

Dry-season baseflow	**Longitudinal Connectivity**	
	Low	High
Low	0.95	0.05
High	0.05	0.95

Table B29. Conditional probability table (Scenario B, Middle) for the Diseased Individuals node

Temperature (ADM)	**Diseased Individuals (proportion)**	
	Low	High
Low	0.95	0.05
High	0.05	0.95

Table B30. Conditional probability table (Scenario B, Middle) for the Fish Growth node

Fine Sediment	**Fish Growth**	
	Low	High
Low	0.05	0.95
High	0.95	0.05

Table B31. Conditional probability table (Scenario B, Middle) for the Food Supply node

Algae Bloom	**Food Supply**	
	High	Low
Large	0.95	0.05
Small	0.05	0.95

End Node

Table B32. Conditional probability table (Scenario B, E1) for the Juvenile Steelhead Condition node under assumptions that longitudinal connectivity is the limiting factor

Food supply	Fish growth	Long. connectivity	Diseased individuals	**Juvenile Steelhead Condition**		Source	Justification
				Good	Poor		
High	Low	Low	Low	0.20	0.80	Authors' judgement	If longitudinal connectivity is "desirable" (i.e., high), there is a 70% likelihood of "good" juvenile steelhead conditions, even if other variables are undesirable. If long. connectivity is desirable (high) and 2 or more other variables are desirable, the likelihood of "good" juvenile steelhead condition increases to 80%. If long. connectivity is low (even if other variables are desirable), the likelihood of "good" steelhead condition is 20%.
High	Low	Low	High	0.20	0.80		
High	Low	High	Low	0.80	0.20		
High	Low	High	High	0.70	0.30		
High	High	Low	Low	0.20	0.80		
High	High	Low	High	0.20	0.80		
High	High	High	Low	0.80	0.20		
High	High	High	High	0.80	0.20		
Low	Low	Low	Low	0.20	0.80		
Low	Low	Low	High	0.20	0.80		
Low	Low	High	Low	0.70	0.30		
Low	Low	High	High	0.70	0.30		
Low	High	Low	Low	0.20	0.80		
Low	High	Low	High	0.20	0.80		
Low	High	High	Low	0.80	0.20		
Low	High	High	High	0.70	0.30		

Table B33. Conditional probability table (Scenario B, E2) for the Juvenile Steelhead Condition node under assumptions that food supply and fish growth are the limiting factors

Food supply	Fish growth	Long. connectivity	Diseased individuals	**Juvenile Steelhead Condition**		Source	Justification
				Good	Poor		
High	Low	Low	Low	0.70	0.30	Authors' judgement	If both fish growth and food supply are desirable (i.e., high), the likelihood of "good" steelhead condition is 80%. If only one out of the two (fish growth or food supply) are desirable and one or more other condition are desirable, the likelihood of "good" steelhead condition is 70%. If only one of fish growth or food supply are desirable, and no other conditions are desirable, the likelihood of a good steelhead outcome is 60%. If food supply and fish growth are undesirable (even if other variables are desirable), the likelihood of "good" steelhead condition is 30%.
High	Low	Low	High	0.60	0.40		
High	Low	High	Low	0.70	0.30		
High	Low	High	High	0.70	0.30		
High	High	Low	Low	0.80	0.20		
High	High	Low	High	0.80	0.20		
High	High	High	Low	0.80	0.20		
High	High	High	High	0.80	0.20		
Low	Low	Low	Low	0.30	0.70		
Low	Low	Low	High	0.30	0.70		
Low	Low	High	Low	0.30	0.70		
Low	Low	High	High	0.30	0.70		
Low	High	Low	Low	0.70	0.30		
Low	High	Low	High	0.60	0.40		
Low	High	High	Low	0.70	0.30		
Low	High	High	High	0.70	0.30		

Table B34. Conditional probability table (Scenario B, E3) for the Juvenile Steelhead Condition node under assumptions that Disease is the limiting factor

Food supply	Fish growth	Long. connectivity	Diseased individuals	**Juvenile Steelhead Condition**		Source	Justification
				Good	Poor		
High	Low	Low	Low	0.70	0.30	Authors' judgement	If disease is desirable (i.e., low), there is a 70% likelihood of "good" juvenile steelhead conditions, even if other variables are undesirable. If disease is desirable (low) and 2 or more variables are desirable, the likelihood of "good" steelhead condition increases to 80%. If disease is undesirable (high), the likelihood of "good" steelhead condition is 30% (even if other variables are desirable).
High	Low	Low	High	0.30	0.70		
High	Low	High	Low	0.80	0.20		
High	Low	High	High	0.30	0.70		
High	High	Low	Low	0.80	0.20		
High	High	Low	High	0.30	0.70		
High	High	High	Low	0.80	0.20		
High	High	High	High	0.30	0.70		
Low	Low	Low	Low	0.70	0.30		
Low	Low	Low	High	0.30	0.70		
Low	Low	High	Low	0.70	0.30		
Low	Low	High	High	0.30	0.70		
Low	High	Low	Low	0.70	0.30		
Low	High	Low	High	0.30	0.70		
Low	High	High	Low	0.80	0.20		
Low	High	High	High	0.30	0.70		

Scenario B runs in R

Table B35. Scenario B probability combinations

Run #	Hydrologic Nodes	Middle Nodes		End Node
		Level 2 uncertainty	Level 3 uncertainty	
1	Moderate	Base	Base	Base
2	Wet-Dry	Base	Base	Base
3	Dry	Base	Base	Base
4	Wet	Base	Base	Base
5	Moderate	Base	Increased certainty	Base
6	Wet-Dry	Base	Increased certainty	Base
7	Dry	Base	Increased certainty	Base
8	Wet	Base	Increased certainty	Base
9	Moderate	Base	Base	E1
10	Wet-Dry	Base	Base	E1
11	Dry	Base	Base	E1
12	Wet	Base	Base	E1
13	Moderate	Base	Base	E2
14	Wet-Dry	Base	Base	E2
15	Dry	Base	Base	E2
16	Wet	Base	Base	E2
17	Moderate	Base	Base	E3
18	Wet-Dry	Base	Base	E3
19	Dry	Base	Base	E3
20	Wet	Base	Base	E3
21	Moderate	Base	Increased certainty	E1
22	Wet-Dry	Base	Increased certainty	E1
23	Dry	Base	Increased certainty	E1
24	Wet	Base	Increased certainty	E1
25	Moderate	Base	Increased certainty	E2
26	Wet-Dry	Base	Increased certainty	E2
27	Dry	Base	Increased certainty	E2
28	Wet	Base	Increased certainty	E2
29	Moderate	Base	Increased certainty	E3
30	Wet-Dry	Base	Increased certainty	E3
31	Dry	Base	Increased certainty	E3
32	Wet	Base	Increased certainty	E3