Decision support tools for waterway managers: Spatially explicit data, models, engagement, and monitoring

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Abstract: Waterway managers face complex challenges in protecting and enhancing the health and social benefits of freshwater systems from a range of current and future threats, including climate change and urbanization. Key questions that need to be addressed by waterway managers include relative importance of future threats, where to focus limited resources, what actions are likely to result in measurable benefits, how to set meaningful targets, and how to integrate and achieve system-scale outcomes. This paper presents 5 key tools in a proposed decision support system (DSS) to enable waterway managers to identify needs, then assess and prioritize interventions throughout a spatially explicit stream network using geospatial data, modeling, stakeholder engagement, decision-making, and monitoring to optimize cost-effective management actions. Through case studies from diverse regional waterway management agencies in Australia (Melbourne, Victoria) and the United States (Denver, Colorado; Southern California; and Austin, Texas), we compare approaches that include habitat suitability models, physics-based watershed models, and predictive analytics to guide intervention strategies, resulting in more efficient, effective, and equitable waterway management decisions. The proposed DSS emphasizes the importance of connectivity, scale, and spatial context in stream management, enabling managers to predict outcomes, set quantitative targets, and more clearly communicate benefits to stakeholders. By harnessing objective data in service of social values, the tools presented and a DSS approach helps overcome potential technical, economic, and social challenges by improving decision-making rigor and transparency, supporting accountability and adaptive management, and fostering trust through the reproducibility of decision processes.

Key words: water resource management, watershed modeling, urban ecosystems, stream network, social values, watershed tools

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Received 26 May 2025; Accepted 16 May 2026; Published online 22 July 2026; Associate Editor, Krista Capps

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INTRODUCTION

Waterway managers, the people and organizations responsible for protecting and improving the social, economic, and environmental benefits that waterways provide, face a complex and dynamic set of tasks (Ladson et al. 1999, Walsh et al. 2005, Prosser et al. 2015). Fundamental to this role is the need to understand 1) Where should we focus management efforts? 2) What management actions are most likely to be beneficial in each location? 3) How do we understand potential risks from future threats such as climate change and urban growth? 4) How do we set meaningful management targets at the right scale? and 5) How do multiple projects function together to create system-scale outcomes? In stream systems, as in many other environments, the question of *where* to act may be just as important as *what* action to implement. Waterway managers need approaches which can parse a potentially overwhelming diversity of stream types, scales, conditions, and threats, and focus attention where it can have the greatest benefit relative to the cost of a waterway management intervention (e.g., Steel et al. 2008). Questions of scale and connectivity are important when considering stream networks, where intervention success may be highly dependent on connectivity to other interventions (e.g., protection of headwater streams at scale, removal of barriers to fish migration, restoration of riparian corridors). With finite resources, waterway managers, often working at the watershed scale, need decision support tools to prioritize actions and their spatial arrangement (Reynolds et al. 2008).

Here we illustrate the application of waterway intervention decision support systems (DSSs) based on spatially explicit data and models. An intervention in the context of this paper is any action taken by a waterway manager to change environmental or social outcomes in a favorable direction. It can be a project, program, or regulation (see Herrington et al. 2026 for a detailed discussion of interventions). Applied as part of a strategic planning framework (Herrington et al. 2026), spatially explicit DSSs can help waterway managers understand the complex systems they work with, reduce uncertainty, and move forward with interventions based on best-available, but imperfect, data (Sànchez-Marrè et al. 2006). In the most effective examples, DSSs and their integrated tools underpin the identification, assessment, and prioritization of stream intervention activities at the right scale and level of detail for the types of decisions they support. In particular, spatial frameworks in DSSs can provide visual representations that improve communication of decision benefits and costs both at big-picture, regional scales and granular site-specific scales. Similarly, DSSs can integrate public and stakeholder aspirations by applying larger weights in the model inputs to strongly held community values. These tools also allow for the integration of quantitative analysis and qualitative stakeholder input, weighting, and prioritization, but ideally in the context of decision support, not rigid decision adoption (Janssen 1992).

In this paper, we outline key considerations for designing robust spatial planning tools, drawing on several examples of successful development and application of spatially explicit DSSs to support intervention planning, target setting, and monitoring. This article is intended to provide insights to decision makers on opportunities and challenges when designing or improving spatially explicit DSSs. The ideas and direction of this paper came together during a knowledge-sharing workshop held at The University of Melbourne in Burnley, Victoria, Australia, in 2023. The 15 participants, from Australia (Melbourne, Victoria) and the United States (Austin, Texas, and Denver, Colorado), quickly identified common approaches, challenges, and opportunities across regions. Evolving from this initial inspiration, 3 follow-up workshops held virtually over the summer of 2024, each attended by ~10 participants from the same group, incorporated further perspectives from Southern California and established the goal of sharing lessons learned with other water managers worldwide. Specifically, this article explores how a spatially explicit DSS can be used by waterway managers to identify the most cost-effective suite of management actions across their area of operation. These tools help identify priorities about *where* to intervene and *what* interventions to undertake for the greatest benefit to region-wide waterway health in the face of current and future threats.

TOOLS AND APPLICATION

During a series of workshops in 2024, the authors proposed a generalized structure for DSSs for waterway managers (Fig. 1) made up of 5 key components, or tools, within a structured decision-making framework (SDM; Gregory et al. 2012, Hemming et al. 2022). These tools incorporate a geospatial database that encodes stream network relationships (see the Geospatial tools section, e.g., the National Hydrography Dataset [NHD]; McKay et al. 2012). Spatial data, along with relevant environmental data, are used to build robust system-based models (see the Modeling tools section). Modeling is integrated into an explicit decision-framing process that guides intervention identification, scenario planning, cost–benefit analysis, and prioritization (see the Decision-informing tools section). Communication and engagement tools are integrated for knowledge sharing and stakeholder participation (see the Communication and engagement tools section). Monitoring data verify that the models and geospatial tools are fit for purpose and that predictions of intervention benefits are robust (see the Monitoring tools section). Each of these components is important as part of a DSS (Fig. 1), which can have a variety of forms and structures, each with their own advantages and limitations within decision science (Hemming et al. 2022).

Overview of case studies

Although routine environmental monitoring and land-use data were often the historic basis for waterway management

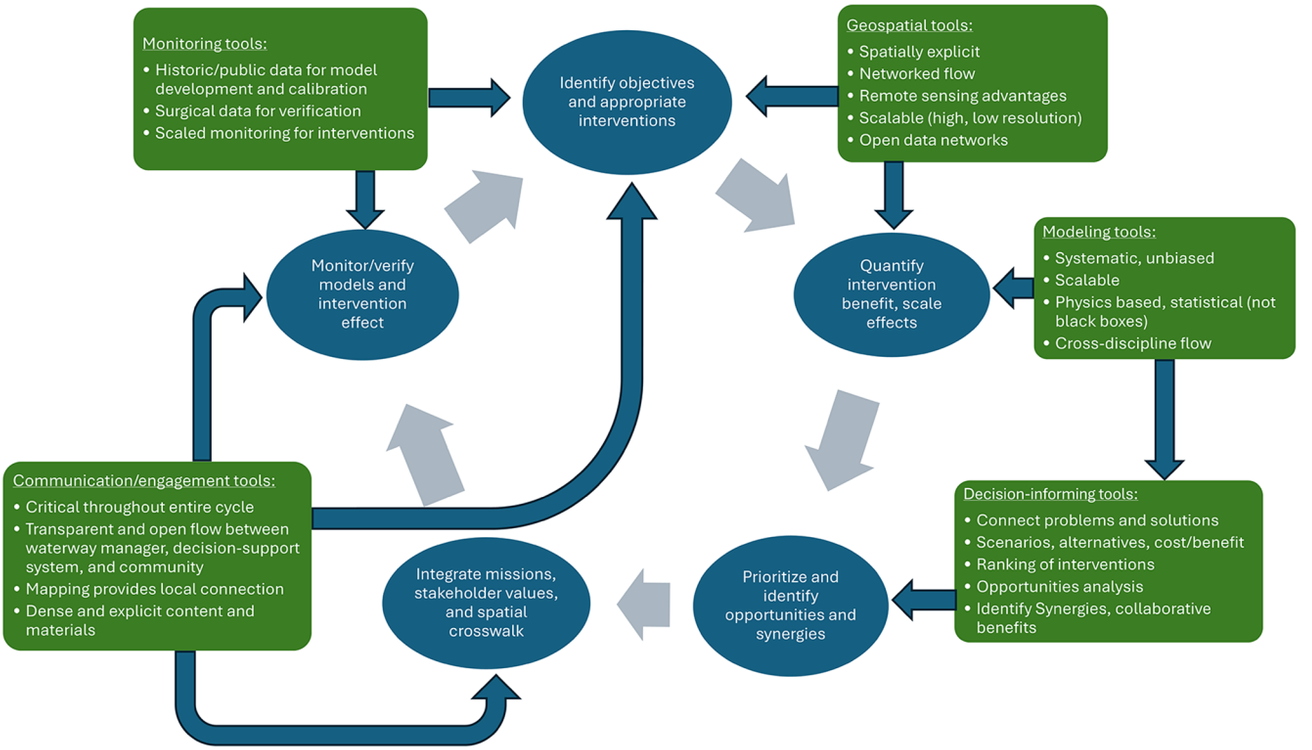


Figure 1. The 5 key tools (green boxes) in the waterway managers' decision support system and how they are utilized and drive an adaptive, recursive, and cyclical-structured decision-making cycle (blue circles). Gray arrows show the adaptive cycle and blue arrows suggest where the tools are most directly relevant to the cycle, but note that where the tools are used is flexible and may not be only in 1 place (e.g., the communication and engagement tools, which may be used throughout the entire cycle).

decision-making in much of the United States and Australia, we describe case studies that incorporate the coupling of spatial data, models, engagement, and monitoring that provide some important advantages for waterway managers (Box 1). This paper reviews each of the 5 key DSS tools noted above with reference to the 4 case studies of spatially explicit DSSs around the world with which the authors have direct experience (Table 1). The case studies were selected to cover a range of contrasting contexts, including geographic region, geographic extent, type of geospatial and modeling tools used, nature of their application to waterway management decision-making, stakeholder engagement, and monitoring. In Melbourne, the Healthy Waterways Strategy uses spatially explicit stream networks and habitat suitability models (HSMs) toward the goal of selecting stormwater and riparian waterway interventions in the most effective combination. The Mile High Flood District (MHFD) in Denver developed a geomorphic typology system with the goal of assessing stream reach physical condition and community values in a large and diverse jurisdictional region. The Stream Classification and Prioritization Explorer (SCAPE) prioritization tool in Southern California uses publicly available spatial data and predictive analytics to estimate biological condition in reaches where empirical data are not available and estimate baseline conditions under different levels of watershed development, providing resource effective prioritization of restoration work. In Austin, the Watershed Health Decision Support System integrates high-resolution spatial data with physics-based watershed models to identify optimized combinations of restoration solutions at parcel, reach, and catchment scales. We use each of these contrasting case studies to illustrate the application of our DSSs for waterway managers, including across each of the 5 key components, namely, the geospatial, modeling, decision-informing, communication and engagement, and monitoring tools.

Geospatial tools

An essential starting point for developing spatially explicit DSSs are geospatial tools, such as robust, data-rich geographical information systems (GISs). Incorporating a GIS that includes stream networks and remote sensing greatly increases the power of spatial data, resulting in improved understanding of the wide variety of landscape variables (e.g., Hall and Azad Hossain 2020). In a high-resolution spatial database that includes flow paths, land use, and land cover information, a wide range of environmental health indicators can be identified, including riparian and impervious cover, flow and reach connectivity, catchment area, and

Box 1

Advantages of robust spatially explicit decision support system (DSS), developed during a series of 3 coauthor workshops in the summer of 2024.

1) Consolidates existing stream data and knowledge needed to support decision-making into a single spatial network that can be built upon and adapted iteratively.
2) Identifies stressor–response relationships between landscape variables and aspects of waterway health, providing insights into the relative benefits of contrasting interventions.
3) Estimates waterway condition and values at locations where monitoring data are not available using models.
4) Identifies the most cost-effective suite of management actions across regional networks.
5) Incorporates subjective, values-based input from community stakeholders into a transparent and analytical decision-making framework that validates and quantifies inputs for open communication between the waterway manager and stakeholders.
6) Provides rich data on spatial context to assist in the setting of quantitative management targets for more efficient monitoring and evaluation of interventions.
7) Supports performance and business cases for effective allocation of waterway improvement resources.

infrastructure (culverts, stormwater pipe outfalls, etc.) that can be powerful predictors of key environmental goals or outcomes, and drive intervention selection. For example, the City of Austin has used available remote sensing data (e.g., Nearmap, Bangaroo, New South Wales, Australia) to calculate the percentage of canopy cover, impervious cover, and pervious cover in floodplains to serve as a novel indicator of stream health at a municipal scale (Scoggins et al. 2021). An additional benefit of having robust spatial data is to provide inputs to models that can help develop predictive relationships between stressors and response variables. The amount of impervious cover or specific land uses can be influential drivers of watershed health and can be readily quantified at different scales, and linked to drainage networks (e.g., Walsh 2023), as was demonstrated in the MHFD case study (Denver; Table 1). The results of this study demonstrated strong links between stream condition and urban land cover as well as between population density and impervious area (Murphy et al. 2025). The DSS example from Southern California makes use of readily available public datasets, such as the National Hydrography Dataset (NHD; McKay et al. 2012) and StreamCat (Hill et al. 2016). These resources can address many of the geospatial needs of waterway managers in the continental United States at no cost to users, and similar resources are available in much of the world. In Melbourne, substantial investment was needed over multiple years to develop accurate stream network and subcatchment mapping, including a library of associated environmental information (e.g., vegetation cover, impervious cover, temperature, modeled runoff depth) for over 8000 stream reaches with a median stream length of ~1 km (Coleman et al. 2018, Walsh 2023). Our case studies highlight how spatially explicit, network-focused geospatial tools can integrate datasets into the DSS (Fig. 1) and provide a foundation for objective setting and modeling efforts.

Modeling tools

Geospatial data can serve as inputs into models of stressor–response relationships. Many modeling software programs, such as Soil and Water Assessment Tool (SWAT), Gridded Surface Subsurface Hydrologic Analysis (GSSHA), and United States Geological Survey's open-source, modular hydrologic software (MODFLOW) routinely allow for these types of inputs. The level of model-building effort can span between parsimonious, data-driven statistical models to complex physics-based models (Harris et al. 2023), depending on the needs and resources of the users. At the more complex end of this modeling continuum, the City of Austin built 2D gridded watershed models to estimate the change in hydrology associated with impervious cover for any point in a drainage network (Porras et al. 2025). This example highlights the contribution of physics-based models with geographic data to identify specific areas of infiltration deficiency for focused intervention and how existing GIS data at large spatial scales can be utilized to inform decision-making at multiple scales (e.g., site, reach, and catchment scales). On the other end of the spectrum, empirical data can be used to formulate stressor–response relationships using traditional statistical techniques or machine learning algorithms to develop a more parsimonious model than physics-based models, which can still be spatially explicit and include stream network connectivity (e.g., spatial statistical stream network models; Peterson and Ver Hoef 2010). Southern California's SCAPE

Table 1. Case studies of spatially explicit planning and 5 key tools that make up the decision support systems in the United States and Australia. MHFD = Mile High Flood District, SCAPE = Stream Classification and Prioritization Explorer, NHD+ = the National Hydrography Dataset Plus, StreamCat = Stream-catchment dataset.

Location	Melbourne, Australia	Denver, Colorado	Southern California	Austin, Texas
Case study	Healthy waterways strategy, spatially explicit modeling, and prioritization (Melbourne Water 2018a)	MHFD broad-scale stream condition assessment and geomorphic-based reach typology	SCAPE tool (Beck et al. 2019, 2020)	Environmental Integrity Index, Watershed Health Decision Support
Purpose	Provide predictions of biotic conditions across a region and under different scenarios to support prioritization of interventions that aim to protect and improve stream health under future threats.	Provides an overall evaluation of physical conditions leveraging stream typology to evaluate downstream patterns, response potential, and evolutionary trajectory.	Provide expected ranges of biological conditions for both sampled and unsampled catchments. Sites that substantially deviate from predictions (i.e., over- or underperforming sites) are flagged for further actions (e.g., restoration, causal assessment, protective assessment).	Identifies environmental problem areas every kilometer along every waterway in Austin, prioritizes these areas, and provides a strategic and effective suite of solutions.
Geospatial	Mapping of stream network and subcatchments and compilation of environmental variables in a spatially explicit database (Walsh 2023). Environmental variables are mapped to the stream network, accounting for connectivity and distance attributes (e.g., connected imperviousness, fish barriers, proximal riparian forest cover), and key variables are available for both the local subcatchment and the cumulative upstream catchment.	Leveraging a custom stream network and subcatchments to assess the condition of ~4000 km of streams through the lens of 5 elements: community values, hydrology, hydraulics, geomorphology, and vegetation. A companion remote-sensed reach-scale classification method promotes integrated understanding of urban stream physical character and behavior and the associated management implications.	Models are built off the NHD+ flowline dataset and the associated geospatial data in the StreamCat dataset (https://www.epa.gov/national-aquatic-resource-surveys/streamcat-dataset; Hill et al. 2016). Reaches not represented/incorrectly represented in NHD+ are therefore excluded.	The geospatial environment provides input layers, such as land use, impervious cover, geology, and soil types, for physics-based modeling. It is also used for displaying dashboards of the modeled environmental results.
Modeling	Individual habitat suitability models (using boosted regression trees) for 52 macroinvertebrate families, 13 native fish species, and the Platypus *Ornithorhynchus anatinus*. These models predicted reach-scale habitat suitability for each of the modeled taxa across the 8200+ reaches in the nearly 13,000-km^2 region (Chee et al. 2020, Coleman et al. 2022).	Open-space access, land use, floodplain connectivity, and sediment-supply modeling are inputs into the assessment approach. The outcomes provide an overall evaluation of physical conditions and community values based on various types of spatial and temporal physical function and social–ecological quality data.	Landcover parameters from StreamCat are the model inputs (quantile random forest). Model outputs are predicted ranges of bioassessment index scores, applied to all stream segments in NHD+ (McKay et al. 2012). Key points within the range (e.g., 10th, 50th, 90th percentiles) are compared to assessment thresholds to classify reaches as "likely constrained", "likely unconstrainted", etc.	The modeling environment is a 2D gridded physics-based watershed model (Porras et al. 2025). It uses geospatial and meteorological data to simulate overland flow and stream flow over the course of 1 y for every creek in Austin.

Table 1. (*Continued*)

Location	Melbourne, Australia	Denver, Colorado	Southern California	Austin, Texas
Decision-informing	Two-step process, first identifying the most cost-effective action at any given reach, followed by spatial prioritization using Zonation to rank the 8200+ stream reaches across the landscape in order of priority for intervention (Chee et al. 2020).	Data-driven decisions: remote sensing based on reach-scale, functional condition scoring provides a dynamic mapping environment for planning and management decision-making.	For unsampled reaches, model outputs can be used to identify sites that are likely to be in good/poor condition. For sampled reaches, observed scores are compared with model outputs to identify those that score within/above/below expected ranges and prioritize these for different actions.	The modeled environment provides decision makers with a map of problem areas and their specific problem. From this, solutions to the problem are proposed and simulated in the model to determine the cost–benefit balance of each proposed solution.
Engagement and communication	Co-designed catchment program included workshops and forums at which spatially explicit modeling was used as 1 input, along with local knowledge and expertise, to support community co-design decisions about management priorities (Melbourne Water 2018b). Public-facing website with spatial mapping of habitat suitability and prioritization results.	Pilot testing across multiple watersheds and communities with input from local governments, and agency partners through stakeholder outreach. Public-facing website with spatial mapping of condition assessment and reach typology that includes urban characteristics such as near natural or channelized for all reaches in the stream network.	Watershed-scale dashboards have been developed to help decision makers set priorities for their sites (https://sccwrp.shinyapps.io/scape/). Outputs have been included in other (larger-scale) dashboards to provide additional context for interpreting monitoring results. (https://sccwrp.shinyapps.io/sqi_shiny_dynamic/)	Watershed-scale dashboards based on monitoring and modeling outputs depict the areas with overlapping problems and the severity of the problems.
Monitoring	Spatially explicit modeling supports monitoring through the selection of 1) eDNA monitoring sites that achieve moderate to strong statistical power in detecting changes in macroinvertebrate, fish, and platypus occupancy (Tingley et al. 2020); 2) macroinvertebrate sampling sites across gradients of important environmental conditions (imperviousness, forest cover, and climate) while also preserving existing long-term sites; 3) fish-catch monitoring sites in expected habitats for priority species (Melbourne Water 2019).	Field verification prioritizes checking metrics that can be difficult to score using aerial photographs, such as geomorphic properties (e.g., depositional reaches), bank stability, and riparian vegetation width. Field verification used to clear up instances of uncertainty and to calibrate scoring guidelines. Ongoing monitoring of field verification sites and updates to the stream condition assessment results.	Bioassessment data are collected under a range of programs, including statewide and regional ambient monitoring programs, as well as permit-mandated compliance monitoring. Follow-up monitoring distinguishes long-term and transient deviations from predicted conditions.	The monitoring environment validates the modeled outputs. Empirical data are collected on the hydrology, chemistry, and biology of the stream at randomized discrete points, which significantly reduces effort and creates robust predictive ability.

tool (Beck et al. 2019) is based on a relatively simple random forest model that predicts ranges of bioassessment index scores based on their empirical relationship with land cover in the watershed and catchment. When the model is applied to the StreamCat dataset, ranges are then predicted for all stream segments in the state, and these predictions provide managers with spatially explicit estimates of biological integrity in their region, including in unsampled systems. In Melbourne, using long-term (20+ years) environmental survey data and environmental predictor information for the entire stream network, a boosted regression tree modeling approach was used to develop HSMs for 52 macroinvertebrate families, 13 native fish species, and the Platypus *Ornithorhynchus anatinus* (Coleman et al. 2018, Chee et al. 2020). HSMs identify relationships between sites where a species is detected or not detected and the corresponding environmental predictors to make quantitative predictions of the probability of occurrence at other sites. HSMs enabled the quantification and visualization of instream biodiversity value at the reach scale, including the likely benefits of management interventions in isolation and in combination (e.g., stormwater management, riparian revegetation). The modeling tools discussed in these case studies integrate a wide range of complex information into systematic, scalable, and iterative systems that can then frame and guide decision makers toward more objective and effective resource management (Table 1).

Decision-informing tools

Spatially explicit models support data-driven decision-making. Importantly, the objectives of the decisions must come first. Commonly, decision support systems involve cost–benefit analysis (Melbourne and Austin; Table 1), which allows decision makers to see where in a stream network actions are likely to be most cost-effective based on upstream interactions from the model and stressor–response relationships. This analysis of spatially explicit models goes beyond a comparison of the cost-effectiveness of different types of interventions and can elucidate complex dynamics associated with spatial stream patterns, such as the benefits of intervening at headwaters vs larger streams (Melbourne; Table 1), or the benefits of multiple connected interventions along a stream (Austin, e.g., removal of barriers; Table 1). Models can also inform decision-making to identify locations for further investigation. That is, models can provide predictions of degraded conditions in unmonitored reaches, or comparison of monitoring data to predictions to identify surprisingly good or poor biological conditions relative to other reaches with similar levels of watershed alteration (e.g., Southern California; Table 1). Additionally, the results from the models can be statistically analyzed for trends or to determine whether environmental phenomena are within acceptable ranges or control points (Shewhart 1931). Finally, spatially explicit models can support better selection of monitoring sites across gradients of important environmental conditions or in expected habitat areas. For example, the Melbourne habitat suitability modeling supported selection of new eDNA monitoring sites which achieve moderate to strong statistical power of detecting changes in macroinvertebrate, fish, and platypus occupancy (Tingley et al. 2020). The City of Austin's DSS begins with geospatial data from digital elevation maps, soil surveys, and aerial imagery as inputs to the physics-based GSSHA modeling tool. These inputs, particularly impervious cover from image data, serve as stressors to produce hypothetical outputs anywhere along the stream network (Porras et al. 2025) which, for example, could identify specific areas of flashiness or lack of baseflow, values which could then be presented to and prioritized by waterway managers and policymakers. Decision-informing tools provide the transition from empirical or modeled data into evaluating cost–benefit, ranking, and prioritizing interventions, and allow for higher confidence in engagement and implementation (Fig. 1, Box 1).

Communication and engagement tools

Communication and engagement are critical for balanced social–ecological outcomes in waterways (Scoggins et al. 2025), particularly collaborative identification of objectives. This topic is more closely examined in Herrington et al. (2026). Spatially explicit DSSs are particularly effective at facilitating communication of complex waterway health data. The mapped outputs of models can support engagement and communication with neighborhoods, nonprofits, valued stakeholders, and others that are part of the waterway community (Yaryan Hall and Bledsoe 2023, Herrington et al. 2026). For instance, local communities are often interested in specific locations and experience waterways at a granular scale. Mapping allows diverse stakeholders to respond to modeled predictions and share knowledge and information at the scales and scope that is important for them. Objectives used to select optimal interventions (which could be the output of DSSs) must be relevant to the waterway community and waterway manager and capable of being measured and integrated back into the structured decision-making cycle (Fig. 1). The challenge for modelers and decision makers is how to select and distill outputs of complex models and decision support tools into formats that are relevant to the community to enable meaningful public engagement, and vice versa. DSSs are most successful when they include communication tools that are intentionally designed and involve the waterway community in its development. The City of Austin's Rain to River plan solicited information from its residents on intervention preferences, such as delivering a small number of expensive projects vs many inexpensive programs. Based on these social surveys, various waterway management intervention scales can be assessed against their cost (Austin; Table 1).

In Melbourne's Healthy Waterways Strategy development process (Melbourne; Table 1), maps were used in multiple, staged workshops to share the waterway managers'

understanding and predictions concerning macroinvertebrates, fish, and platypuses in streams throughout the region, expectations under climate change and urbanization scenarios, and the effectiveness of different interventions. Analytically identified priority interventions were combined with local knowledge and expertise of stakeholders to ultimately determine priorities. A crucial aspect of effective stakeholder engagement is that this engagement takes place through the entire duration of the project and beyond, not simply after the technical work has been completed (Hampton et al. 2015, Beck et al. 2020, Herrington et al. 2026). In the Southern California example, much of this input was provided by a collaboration of permitted stormwater dischargers, regulatory agencies, and community groups that provided guidance on a range of topics, such as the kinds of data that would be appropriate to include in model development, which thresholds should be used to classify streams, and what types of management actions should be considered at streams in each classification (Beck et al. 2020). The case studies presented here demonstrate the value and application of deep and perennial engagement and communication (Table 1), which is central to a robust waterway management framework (Coleman et al. 2026, Herrington et al. 2026).

Monitoring tools

Existing and historic monitoring data can initially be used to develop and calibrate the models. Independent monitoring data can then be used to validate the models. An increase in both temporal and spatial resolution of data and predictions can be achieved in a stream network through the interaction of monitoring and modeling, where sparse monitoring results can inform models, which then enhance the monitoring program with results at a finer scale. This adaptive cycle between monitoring and modeling results in robust predictive ability for the waterway manager, providing solutions better aligned with waterway-scale visions of success that help reduce tradeoffs between spatial and temporal monitoring resolution. For example, the City of Austin used 20 y of monitoring data from sites that were several kilometers apart to develop and calibrate a model relating the hydrology of the creek to benthic macroinvertebrate community metrics (Porras et al. 2025). This model predicted the same metrics for every kilometer of Austin's streams. This model will be validated with future targeted monitoring and further refine benthic macroinvertebrate community scores at any location in the stream network without labor-intensive routine sampling surveys (Austin; Table 1).

In addition to using monitoring to calibrate and validate models, over time monitoring can play an important role in understanding the waterway health outcomes from certain interventions and track progress toward waterway management visions—ultimately underpinning continuous learning and adaptive management (Herrington et al. 2026). For example, the Healthy Waterways Strategy in Melbourne is supported by a Monitoring, Evaluation, Reporting and Improvement framework and associated Monitoring and Evaluation Plans that track progress toward waterway condition and value management targets, including testing assumptions about the likely benefits of management actions (Melbourne Water 2019). The incorporation of monitoring tools is not new to waterway management, but the ability to identify, target, and scale empirical data collection within a larger DSS framework and create learning loops (Fig. 1) improves efficiency and may provide the ability to enhance resolution and accuracy over time (Peterson and Freeman 2016).

Finally, the potential benefit of deep learning models and artificial intelligence (AI) in supporting these DSSs and their components should be noted. AI tools may dramatically improve the ability to integrate large amounts of spatial, environmental, and social data into waterway improvement decision-making, which can result in better outcomes (Pandey et al. 2023). The City of Austin recently developed a deep learning model to explore the nonlinear relationship between hydrology and biological community metrics (Porras et al. 2025). However, exploring these relationships requires large amounts of empirical data (>200 data points) and new ways to interpret complex, convoluted models (Zheng et al. 2023). Another use of AI is through large language models that can be useful in incorporating and analyzing qualitative observations and text from the deep and long-term community engagement that a waterway management framework requires (Herrington et al. 2026). Convolutional neural networks, another AI method, can also be used to classify land use based on image data, thus improving GIS capabilities (Carranza-García et al. 2019, Chen et al. 2021).

CHALLENGES AND OPPORTUNITIES

Developing robust, spatially explicit decision support tools for waterway management can be a complex and resource-intensive process that requires careful planning and stakeholder engagement to maximize their utility to the waterway manager. In some cases, these tools require large, comprehensive datasets that may take many years to collect, and their development can span multiple years, involving iterative refinement and validation (Coleman et al. 2018, Chee et al. 2020). A key challenge lies in building initial acceptance, or buy-in, in the value of the tools, both within the organizations developing them and among external stakeholders (Coleman et al. 2018). To address this challenge, we recommend a participatory approach that begins with clear communication and alignment on objectives. Open and participatory science is particularly important for environmental management (Hampton et al. 2015, Beck et al. 2020). Consistent with the process for establishing a shared vision for the future of the waterway with stakeholders and assessing intervention options (Herrington

et al. 2026), the process for creating a DSS involves participation with stakeholders to assess the tradeoffs associated with intervention options. Stakeholders need to agree on the context of the decision to be made, for example, will the tool help to distinguish among conflicting intervention priorities, and what is an agreed upon definition of success? To build confidence in the DSS, transparency about the tool's limitations is also important, clearly outlining what it cannot achieve and where supplementary data or local knowledge may be required. This honesty fosters confidence that the outputs of the DSS will be accepted by stakeholders, builds ownership in the DSS, and ensures realistic expectations (Thokala and Madhavan 2018). Finally, although initial tools can be built using existing, and even limited, internal or external datasets, it is crucial to plan for targeted data collection to enhance the tool's long-term capabilities and validate the DSS outputs when modeling is statistical or data-driven (Hazır 2015).

For many waterway managers around the world, the default system of decision-making is based on larger-scale regulatory drivers and very local forces associated with monitoring, climatic events, or stakeholder experiences. This information can be misleading (e.g., historical data that no longer represent conditions under a changed climate), unpredictable (based on factors other than statistical probabilities or physics), biased (reactionary, nonrepresentative reporting), and inefficient (not connecting problems with solutions targeting the underlying root causes). Developing a systems-level approach to decision-making combined with robust technical tools has the potential to make a step change in social–ecological outcomes in the complex and resource-limited world of waterway management (Yaryan Hall and Bledsoe 2023, Menichino et al. 2025). Quantitative tools, including spatially explicit data, GIS, models, machine learning, and artificial intelligence have the potential to provide powerful abilities to integrate larger and more complex input datasets and understand robust cost–benefit relationships (Barfod et al. 2011, Kenney et al. 2012). The goal of waterway decision support should not only try to make good decisions but also to avoid bad ones. For instance, site prioritization tools can help identify obviously ineffective actions or actions proposed purely for opportunism (McKay et al. 2020) or by stakeholders with bias or hidden agendas (Enríquez-de-Salamanca 2018). Tool results may also be caveated or overridden for a variety of valid reasons like local knowledge, qualitative outcomes, or objectives not included in models, so the availability of these tools does not force decision makers to blindly follow the DSS, but also provides boundaries that limit the waterway manager or policymakers from subjectively selecting the answer they want.

Spatially explicit data and decision support tools can be an effective means to identify more transparent, publicly supported, and cost-effective waterway management interventions. For example, in Melbourne, prior to the development of the HSMs and use of Zonation to quantify benefits of management actions (Melbourne Water 2018a, Chee et al. 2020), it was harder to justify the necessary resources to managers (i.e., the consequences of a reduced budget to waterway health across the region could not be quantified or clearly articulated). It was also not possible to set quantitative management targets to communicate the anticipated benefits of the investment to stakeholders and against which meaningful monitoring and evaluation of efforts could be achieved. In the case of Austin, a decision support system was able to group (or cluster) contiguous areas with similar needs at a scale smaller than previously realized, but larger than an individual land parcel. In Southern California, watershed managers overseeing the San Gabriel River used the DSS to evaluate a list of >100 sites with poor bioassessment index scores and prioritize just a handful where scores were substantially lower than expected, primarily in the undeveloped upper watershed (Beck et al. 2020); thus, follow-up verification assessments were prioritized at only these sites. With a robust DSS, waterway managers can more effectively identify the type and location of interventions across a range of spatial scales.

In addition to their decision value, coupled data and modeling systems create pathways to reproducibility, provide a focal point for stakeholder engagement and inter- and transdisciplinary dialog, and establish a framework for learning loop cycles of adaptive management (Fig. 1). In fact, coupled monitoring and modeling can provide a means to dialog about urbanizing watersheds. Models are increasingly being built with stakeholders through participatory processes, which provide a pathway to demystifying the use of models (Herman et al. 2019) and increasing trust between stakeholders and analysts. Data systems can also serve as boundary objects that facilitate knowledge integration and become a pathway to innovation (Caccamo et al. 2023). For instance, the act of a multidisciplinary team creating a modeling system generally requires interdisciplinary dialog among technical team members about what data should be collected and synthesized (Herrington et al. 2026). Similarly, the models can then be used as an interactive means for working with stakeholders and creating transdisciplinary dialog about the relative merits of different management strategies.

Making good environmental management decisions has often hinged on the consideration of empirical data with subjective value systems (Gregory and Keeney 2002, Deason et al. 2010), and coupled data and modeling systems cannot overcome all decision-making challenges in complex urban systems. Furthermore, good models and decisions cannot guarantee good outcomes, particularly in systems with high uncertainty and stochasticity. However, these modeling systems can increase the transparency and reproducibility of decision processes, particularly if principles and methods of open science are embraced (Powers and Hampton 2019). The adaptive management literature has long highlighted the importance of iteratively learning and applying

that knowledge (Fischenich et al. 2019), and models have been emphasized as an important mechanism for enshrining and using knowledge alongside monitoring and management activities (Peterson and Freeman 2016). However, monitoring data can be collected for diverse purposes ranging from compliance to research (van Rees et al. 2022), and jointly undertaking modeling alongside monitoring can lead to more strategic data collection focused on the value of information associated with new data (Herrington et al. 2026). Coupling spatial data and modeling systems provides an important feedback mechanism for creating more effective decision-making environments over time. Coupled data and modeling systems are thus invaluable pathways to effective waterway interventions and improved decision-making through time. In summary, key considerations in building and effectively using robust planning and decision-making tools include 1) the utilization of historic and publicly available spatial data, 2) the ability to evaluate interventions at multiple scales, 3) the integration of different types of interventions, 4) the use of physics-based and statistical modeling to predictively and adaptively optimize scenarios, 5) the use of targeted monitoring to calibrate predictive tools and to verify a priori measures of success, and 6) the importance of transparent communication with stakeholders throughout the entire planning, implementation, and monitoring phases to ensure buy-in and long-term engagement.

ACKNOWLEDGEMENTS

Author contributions: MS, BM, RAC, and KLR conceived the paper. All coauthors participated in the workshops. MS led the writing of the paper with contributions from all authors.

Thank you to River Network, Melbourne Water, The University of Melbourne, and the City of Austin for funding the authors' time to participate in the workshops and contribute to the writing of the paper.

Conflict of interest: The authors declare no conflicts of interest.

LITERATURE CITED

Barfod, M. B., K. B. Salling, and S. Leleur. 2011. Composite decision support by combining cost-benefit and multi-criteria decision analysis. Decision Support Systems 51:167–175.

Beck, M. W., R. D. Mazor, S. Johnson, K. Wisenbaker, J. Westfall, P. R. Ode, R. Hill, C. Loflen, M. Sutula, and E. D. Stein. 2019. Prioritizing management goals for stream biological integrity within the developed landscape context. Freshwater Science 38:883–898

Beck, M. W., C. O'Hara, J. S. Stewart Lowndes, R. D. Mazor, S. Theroux, D. J. Gillett, B. Lane, and G. Gearheart. 2020. The importance of open science for biological assessment of aquatic environments. PeerJ 8:e9539.

Caccamo, M., D. Pittino, and F. Tell. 2023. Boundary objects, knowledge integration, and innovation management: A systematic review of the literature. Technovation 122:102645.

Carranza-García, M., J. García-Gutiérrez, and J. C. Riquelme. 2019. A framework for evaluating land use and land cover classification using convolutional neural networks. Remote Sensing 11:274.

Chee, Y. E., R. Coleman, S. RossRakesh, N. Bond, and C. Walsh. 2020. Habitat suitability models, scenarios and quantitative action prioritisation (using Zonation) for the Healthy Waterways Strategy 2018: A resource document. Melbourne Waterway Research-Practice Partnership Technical Report 20.3. (Available from https://mwrpp.org/wp-content/uploads/sites/8/2020/04/20.3-chee-et-al-2020-hsms-scenarios-quant-action-prioritisation-using-zonation-for-the-healthy-waterways-strategy-2018.pdf)

Chen, L., S. Li, Q. Bai, J. Yang, S. Jiang, and Y. Miao. 2021. Review of image classification algorithms based on convolutional neural networks. Remote Sensing 13:4712.

Coleman, R. A., J. Bonneau, D. G. Bos, M. J. Burns, F. Cherqui, T. D. Fletcher, S. Garvey, K. Horndeski, R. Mazor, B. Murphy, C. Purma III, K. L. Russell, S. Stojkovic, and M. Scoggins. 2026. Insights from long-term collaborative research in waterway management. Freshwater Science 45:XX–XX.

Coleman, R. A., Y. E. Chee, N. Bond, S. RossRakesh, and C. J. Walsh. 2018. Benefits and challenges of incorporating spatially-explicit quantitative modelling and action prioritisation in Melbourne Water's Healthy Waterways Strategy. Proceedings of the 9th Australian Stream Management Conference, 2018, Hobart, Tasmania. (Available from https://www.researchgate.net/profile/Rhys-Coleman-2/publication/327098321_Benefits_and_challenges_of_incorporating_spatially-explicit_quantitative_modelling_and_action_prioritisation_in_Melbourne_Water's_Healthy_Waterways_Strategy/links/5b77ea83a6fdcc5f8b514ab8/Benefits-and-challenges-of-incorporating-spatially-explicit-quantitative-modelling-and-action-prioritisation-in-Melbourne-Waters-Healthy-Waterways-Strategy.pdf)

Coleman, R. A., Y. E. Chee, N. R. Bond, A. Weeks, J. Griffiths, M. Serena, G. A. Williams, and C. J. Walsh. 2022. Understanding and managing the interactive impacts of growth in urban land use and climate change on freshwater biota: A case study using the platypus (*Ornithorhynchus anatinus*). Global Change Biology 28:1287–1300.

Deason, J. P., G. E. Dickey, J. C. Kinnell, and L. A. Shabman. 2010. Integrated planning framework for urban river rehabilitation. Journal of Water Resources Planning and Management 136: 688–696.

Enríquez-de-Salamanca, Á. 2018. Stakeholders' manipulation of Environmental Impact Assessment. Environmental Impact Assessment Review 68:10–18.

Fischenich, J. C., S. J. Miller, and A. J. LoSchiavo. 2019. A systems approach to ecosystem adaptive management: A USACE technical guide. ERDC/EL SR-19-9. United States Army Engineer Research and Development Center, Vicksburg, Mississippi. (Available from https://erdc-library.erdc.dren.mil/items/22a7cf7a-73ac-48d6-9561-6afa5bb0882b)

Gregory, R., L. Failing, M. Harstone, G. Long, T. McDaniels, and D. Ohlson. 2012. Structured decision making: A practical guide to environmental management choices. John Wiley & Sons.

Gregory, R. S., and R. L. Keeney. 2002. Making smarter environmental management decisions. Journal of the American Water Resources Association 38:1601–1612.

Hall, J., and A. K. M. Azad Hossain. 2020. Mapping urbanization and evaluating its possible impacts on stream water quality in

Chattanooga, Tennessee, using GIS and remote sensing. Sustainability 12:1980.

Hampton, S. E., S. S. Anderson, S. C. Bagby, C. Gries, X. Han, E. M. Hart, M. B. Jones, W. C. Lenhardt, A. MacDonald, W. K. Michener, J. Mudge, A. Pourmokhtarian, M. P. Schildhauer, K. H. Woo, and N. Zimmerman. 2015. The Tao of open science for ecology. Ecosphere 6:1–13.

Harris, A., N. Richards, and S. K. McKay. 2023. Defining levels of effort for ecological models. ERDC/TN EMRRP-EM-11. United States Army Engineer Research and Development Center, Vicksburg, Mississippi. (Available from http://dx.doi.org/10.21079/11681/47642)

Hazır, Ö. 2015. A review of analytical models, approaches and decision support tools in project monitoring and control. International Journal of Project Management 33:808–815.

Hemming, V., A. E. Camaclang, M. S. Adams, M. Burgman, K. Carbeck, et al. 2022. An introduction to decision science for conservation. Conservation Biology 36:e13868.

Herman, B. D., S. K. McKay, S. Altman, N. S. Richards, M. Reif, C. D. Piercy, and T. M. Swannack. 2019. Unpacking the black box: Demystifying ecological models through interactive workshops and hands-on learning. Frontiers in Environmental Science 7:122.

Herrington, C. S., K. A. Horndeski, M. Scoggins, R. A. Coleman, D. Bos, K. L. Russell, S. Stojkovic, J. Calmbacher, J. Greet, S. Albornoz, Y. E. Chee, and B. Murphy. 2026. Streamlining waterway management with F.L.O.W.: A strategic planning framework incorporating the community and researchers. Freshwater Science 45:XX–XX.

Hill, R. A., M. H. Weber, S. G. Leibowitz, A. R. Olsen, and D. J. Thornbrugh. 2016. The Stream-Catchment (StreamCat) dataset: A database of watershed metrics for the conterminous United States. Journal of the American Water Resources Association 52:120–128.

Janssen, R. 1992. Multiobjective decision support for environmental management. Springer Science+Business Media.

Kenney, M. A., P. R. Wilcock, B. F. Hobbs, N. E. Flores, and D. C. Martínez. 2012. Is urban stream restoration worth it? Journal of the American Water Resources Association 48:603–615.

Ladson, A. R., L. J. White, J. A. Doolan, B. L. Finlayson, B. T. Hart, P. S. Lake, and J. W. Tilleard. 1999. Development and testing of an Index of Stream Condition for waterway management in Australia. Freshwater Biology 41:453–468.

McKay, L., T. Bondelid, T. Dewald, J. Johnston, R. Moore, and A. Rea. 2012. Page 173 *in* NHDPlus Version 2: User guide. Office of Water, United States Environmental Protection Agency, Washington, DC. (Available from https://www.epa.gov/waterdata/nhdplus-national-hydrography-dataset-plus, accessed May 2026)

McKay, S. K., E. H. Martin, P. B. McIntyre, A. W. Milt, A. T. Moody, and T. M. Neeson. 2020. A comparison of approaches for prioritizing removal and repair of barriers to stream connectivity. River Research and Applications 36:1754–1761.

Melbourne Water. 2018a. Healthy Waterways Strategy 2018-2028. Melbourne Water, Docklands, Melbourne, Australia. (Available from https://www.melbournewater.com.au/about/what-we-do/publications/healthy-waterways-strategy)

Melbourne Water. 2018b. Healthy Waterways Strategy resource document: Supporting the development of the strategy. Melbourne Water, Docklands, Melbourne, Australia. (Available from https://healthywaterways.com.au/resources/documents)

Melbourne Water. 2019. Healthy Waterways Strategy monitoring, evaluation, reporting and improvement framework. Melbourne Water, Docklands, Australia. (Available from https://mwhwsstorage.blob.core.windows.net/files/2021-03/HWS-MERI-framework-V1.1.pdf)

Menichino, G. T., L. E. Abera, T. W. Rickey Jr, S. P. Phillips, and S. K. McKay. 2025. A phased approach to urban stream restoration decision-making in Utoy Creek, Atlanta, Georgia. Land 14:449.

Murphy, B. M., P. A. Nelson, J. Gilbert, and J. Sholtes. 2025. What is an urban riverscape? Typological naming of urban riverscapes to support planning and management. PLOS Water 4:e0000345.

Pandey, D. K., A. I. Hunjra, R. Bhaskar, and M. A. S. Al-Faryan. 2023. Artificial intelligence, machine learning and big data in natural resources management: A comprehensive bibliometric review of literature spanning 1975–2022. Resources Policy 86:104250.

Peterson, E. E., and J. M. Ver Hoef. 2010. A mixed-model moving-average approach to geostatistical modeling in stream networks. Ecology 91:644–651.

Peterson, J. T., and M. C. Freeman. 2016. Integrating modeling, monitoring, and management to reduce critical uncertainties in water resource decision making. Journal of Environmental Management 183:361–370.

Porras, A. A., Y.-H. Jin, E. Peacock, Y. Avila, A. N. Chu, H. Mahaseth, A. L. Santiago, and J. G. Siegmund. 2025. Expanding an urban stream ecological monitoring system with functional data analysis and deep learning. Freshwater Science 44:660–673.

Powers, S. M., and S. E. Hampton. 2019. Open science, reproducibility, and transparency in ecology. Ecological Applications 29:e01822.

Prosser, T., P. J. Morison, and R. A. Coleman. 2015. Integrating stormwater management to restore a stream: Perspectives from a waterway management authority. Freshwater Science 34:1186–1194.

Reynolds, K. M., M. Twery, M. J. Lexer, H. Vacik, D. Ray, G. Shao, and J. G. Borges. 2008. Decision support systems in forest management. Pages 499–533 *in* F. Burstein and C. Holsapple (editors). Handbook on decision support systems 2: Variations. 1st edition. Springer.

Sànchez-Marrè, M., K. Gibert, R. Sojda, J.-P. Steyer, P. Struss, and I. Rodríguez-Roda. 2006. Uncertainty management, spatial and temporal reasoning, and validation of intelligent environmental decision support systems. 3rd International Congress on Environmental Modelling and Software - Burlington, Vermont, USA. (Available from https://scholarsarchive.byu.edu/iemssconference/2006/all/25/)

Scoggins, M., Y. Avila, A. Porras, and W. Burdick. 2021. An index of riparian integrity: A GIS-based tool for assessing city-wide riparian function. RR-20-05. Watershed Protection Department, City of Austin, Austin, Texas. (Available from https://services.austintexas.gov/edims/document.cfm?id=359257)

Scoggins, M., I. C. Barrett, B. I. Margetts, E. Martí, B. M. Murphy, A. H. Roy, R. I. Shear, S. A. Sabat-Bonilla, N. A. Griffiths, V. Nanjappa, K. Mussett, K. M. Stirling, S. Chiblow, and S. Nolan. 2025. An approach to urban waterway assessment using holistic values and reciprocity. Journal of Freshwater Science 44:633–659

Shewhart, W. A. 1931. Economic control of quality of manufactured product. D. Van Nostrand Company.

Steel, E. A., A. Fullerton, Y. Caras, M. B. Sheer, P. Olson, D. Jensen, J. Burke, M. Maher, and P. McElhany. 2008. A spatially explicit decision support system for watershed-scale management of salmon. Ecology and Society 13:50.

Thokala, P., and G. Madhavan. 2018. Stakeholder involvement in multi-criteria decision analysis. Cost Effectiveness and Resource Allocation 16:0.

Tingley, R., C. H. Wu, and A. Weeks. 2020. Developing an optimal eDNA sampling strategy for reporting on environmental values. Report by EnviroDNA for Melbourne Water. EnviroDNA, Brunswick, Victoria, Australia. (Available from Melbourne Water, 990 La Trobe Street, Docklands, Victoria, Australia.)

van Rees, C. B., L. Naslund, D. D. Hernandez-Abrams, S. K. McKay, C. B. Woodson, A. Rosemond, B. McFall, S. Altman, and S. J. Wenger. 2022. A strategic monitoring approach for learning to improve natural infrastructure. Science of the Total Environment 832:155078.

Walsh, C. J. 2023. Melbourne Water stream network: User's manual. Version 1.3. Melbourne Waterway Research Practice Partnership Technical Report 19.4d. Waterway Ecosystem Research Group, School of Agriculture, Food and Ecosystem Sciences, The University of Melbourne, Melbourne, Australia. (Available from https://doi.org/10.26188/26866840)

Walsh, C. J., A. H. Roy, J. W. Feminella, P. D. Cottingham, P. M. Groffman, and R. P. Morgan. 2005. The urban stream syndrome: Current knowledge and the search for a cure. Journal of the North American Benthological Society 24:706–723.

Yaryan Hall, H. R., and B. P. Bledsoe. 2023. Integrated urban riverscape planning: Spatial prioritization for environmental equity. ASCE OPEN: Multidisciplinary Journal of Civil Engineering 1:04023004.

Zheng, H., Y. Liu, W. Wan, J. Zhao, and G. Xie. 2023. Large-scale prediction of stream water quality using an interpretable deep learning approach. Journal of Environmental Management 331:117309.