Towards sustainable water management through optimization: Integrating e-flows and supporting adaptive management

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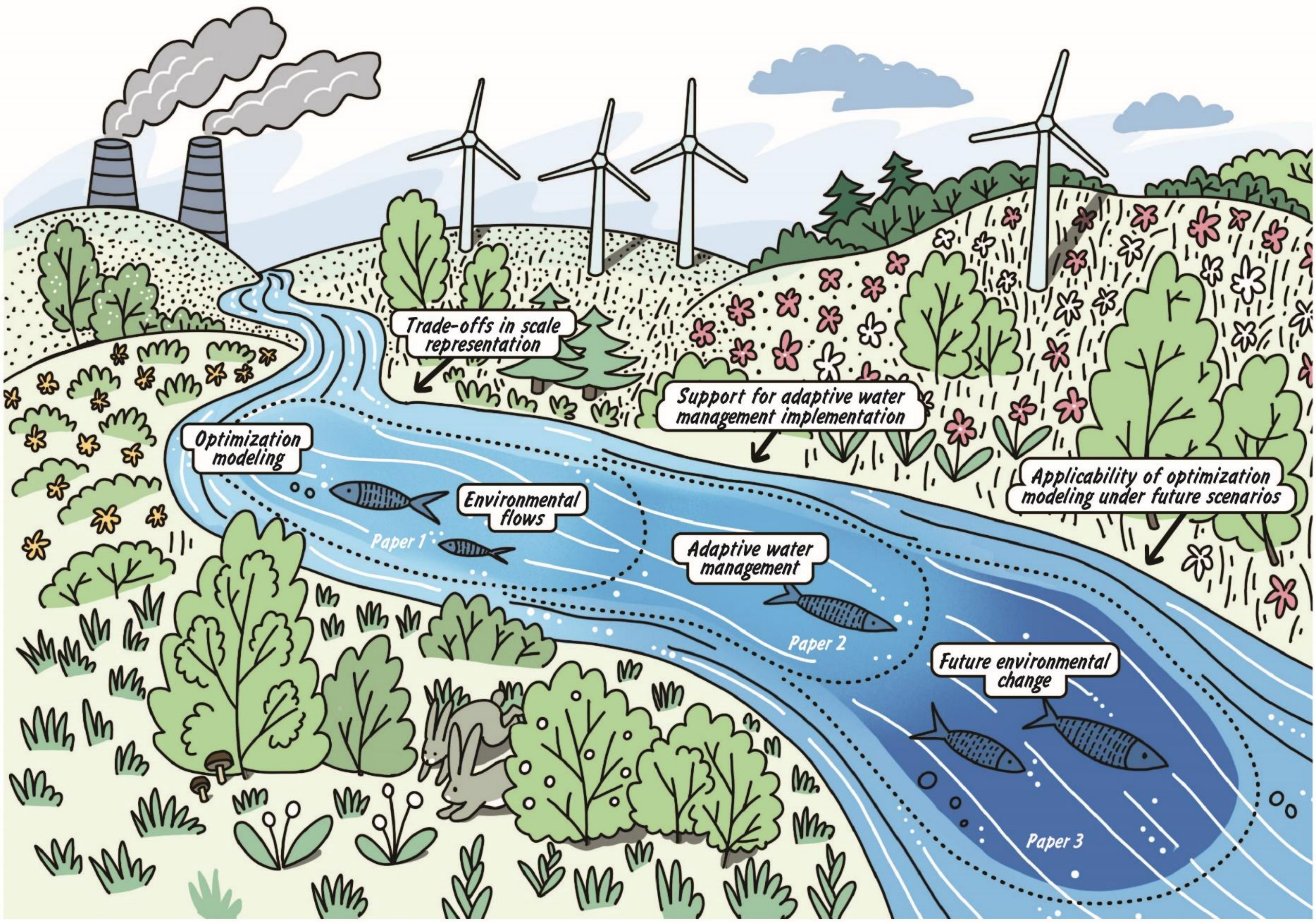
In wilderness is the preservation of the world.
— Henry David Thoreau, *Walden*, 1854

Посвящаю эту работу моему дяде Владику.


Trade-offs in scale representation
Support for adaptive water management implementation
Optimization modeling
Environmental flows
Paper 1
Applicability of optimization modeling under future scenarios
Adaptive water management
Paper 2
Future environmental change
Paper 3

Summary

Water management faces increasing challenges due to environmental changes and competing human demands. In this context, environmental flows (e-flows) are of critical importance as they define the water regimes necessary for maintaining riverine ecosystems. Models have become crucial tools for supporting decision-making in river basin management by enabling sustainable resource allocation considering ecological needs. Optimization modeling is one such approach for addressing the challenges of sustainable resource allocation, although the development of these models faces several obstacles. This thesis investigates the following research topics:

1. Trade-offs in scale representation in optimization modeling for water resource management;
2. Suitability of optimization models for mediating the incorporation of e-flows into management at different scales to support the implementation of adaptive management implementation;
3. Applicability of optimization models at the basin scale under future change.

This dissertation is based on three consecutive articles:

The first research topic is addressed in *Chapter 2* (Paper 1). The chapter presents a literature review to understand and acknowledge the trade-offs in decision-making when applying optimization models for water management at different spatial and temporal scales. It outlines a framework that ties all model-related decisions into practical steps for optimization model development and emphasizes the need for a shift to model perception and model formulation stages, away from solely result-oriented approaches. The chapter provides a series of key questions to support the problem perception and formulation stages to ensure transparency during model development.

The second research topic is expanded in *Chapter 3* (Paper 2) and builds on insights from an optimization assessment developed for a pilot application at various river water diversion sites in the Pas River basin (Northern Spain). The presented study shows how ecological requirements derived by experts can be translated into model parameters to achieve diversion objectives. The procedure can be used to identify the temporal scales in which the major trade-offs in water availability manifest themselves, thus guiding management efforts. In addition, the chapter provides suggestions for the most common challenges and limitations in applicability.

The second and last research topics are addressed in *Chapter 4* (Paper 3), which further evaluates the use of optimization to balance water diversion for human consumption and ecosystem services. This chapter

also examines the potential to integrate future environmental scenarios, such as climate and land use change. An evolutionary optimization model is proposed to guide diversion management in the Pas River basin. The findings from the study can help managers identify and track hotspots in the basin where ecological needs are being lost over different time periods. The chapter provides recommendations to enable the adoption of adaptive management through optimization modeling.

Overall, this thesis provides new insights into the use of optimization modeling to solve problems of sustainable water resource allocation, including the consideration of e-flows. Combining a comprehensive review with a hands-on learning-by-practice modeling approach, the major challenges and limitations in applying optimization models to water resource management are explored with the goal of improving decision-making processes at modeling-management interface.

Zusammenfassung

Das Wasserressourcenmanagement steht zunehmend vor Herausforderungen, die durch Umweltveränderungen und konkurrierende menschliche Ansprüche entstehen. In diesem Zusammenhang spielen ökologische Mindestabflüsse (e-flows) eine zentrale Rolle, da sie die Abflussregimes definieren, die notwendig sind, um Flussökosysteme zu schützen und zu erhalten. Modelle haben sich dabei zu wichtigen Werkzeugen entwickelt, um die Entscheidungsfindung im Flussgebietsmanagement zu unterstützen und eine nachhaltige Verteilung der Ressourcen unter Berücksichtigung ökologischer Anforderungen zu gewährleisten. Optimierungsmodelle stellen eine vielversprechende Herangehensweise dar, um die komplexen Herausforderungen bei der Ressourcenverteilung zu bewältigen. Ihre Entwicklung ist jedoch noch immer mit einer Vielzahl von Herausforderungen verbunden. Diese Dissertation behandelt daher drei zentrale Themen:

- Abwägungen bei der Skalenrepräsentation in der Optimierungsmodellierung für das Wassermanagement;
- Eignung von Optimierungsmodellen zur Integration von ökologischen Mindestabflüssen in das Wassermanagement auf verschiedenen Maßstabsebenen;
- Anwendbarkeit von Optimierungsmodellen auf Einzugsgebietsebene für ein adaptives Management unter zukünftigen Umweltveränderungen.

Die Dissertation basiert auf drei aufeinander aufbauenden wissenschaftlichen Studien:

Das erste Forschungsthema wird in *Kapitel 2* (Paper 1) behandelt. Dieses Kapitel bietet eine Literaturübersicht, um die Abwägungen bei der Entscheidungsfindung durch Optimierungsmodelle, die für das Wassermanagement auf verschiedenen räumlichen und zeitlichen Skalen angewendet werden, zu verstehen und anzuerkennen. Die Studie stellt einen integrativen Rahmen vor, der modellbezogene Entscheidungen in praktische Schritte für die Entwicklung von Optimierungsmodellen überführt. Besonders hervorgehoben wird die Notwendigkeit eines Paradigmenwechsels, weg von rein ergebnisorientierten Ansätzen hin zu einer bewussten Modellwahrnehmung und -formulierung. Das Kapitel stellt Schlüsselfragen bereit, welche die Transparenz und Nachvollziehbarkeit während der Modellentwicklung gewährleisten.

Die Erkenntnisse aus der ersten Studie fließen direkt in das zweite Paper (Kapitel 3) ein. Die Studie basiert auf Erkenntnissen aus einer Optimierungsbewertung, die für eine Pilotanwendung an verschiedenen Wasserumleitungsstandorten im Einzugsgebiet des Pas-Flusses (Nordspanien) entwickelt wurde. Die

vorgestellte Studie zeigt, wie von Experten gestellte ökologische Anforderungen in Modellparameter übersetzt werden können, um Umleitungsziele zu erreichen. Das Verfahren kann verwendet werden, um die zeitlichen Skalen zu ermitteln, in denen sich die wichtigsten Kompromisse bei der Wasserverfügbarkeit manifestieren, um so die Bewirtschaftungsmaßnahmen besser steuern zu können. Darüber hinaus zeigt das Kapitel die Herausforderungen und Grenzen der Anwendbarkeit.

Das zweite sowie das letzte Forschungsthema werden in *Kapitel 4* (Paper 3) behandelt, in dem die Verwendung von Optimierungsmodellen zur Abwägung der Anforderungen an die Wasserumleitung, den menschlichen Verbrauch und den Erhalt von Ökosystemdienstleistungen weiter untersucht wird. Dies erfolgt durch die Untersuchung der Auswirkungen zukünftiger Szenarien von Klima- und Landnutzungsänderungen. Es wird ein evolutionäres Optimierungsmodell vorgeschlagen, um das Wasserumleitungsmanagement im Pas-Einzugsgebiet zu steuern. Die Ergebnisse der Studie können den zuständigen Ämtern und Behörden dabei helfen, kritische Bereiche oder "Hotspots" im Einzugsgebiet zu identifizieren, in denen ökologische Bedürfnisse über verschiedene Zeiträume hinweg verloren gehen. Das Kapitel enthält Empfehlungen, die die Einführung eines adaptiven Managements durch Optimierungsmodellierung ermöglichen sollen.

Insgesamt bietet die Dissertation neue Erkenntnisse zur Anwendung von Optimierungsmodellen bei der Bewältigung von Problemen bei der Umsetzung von Strategien der nachhaltigen Verteilung von Wasserressourcen, einschließlich der Berücksichtigung von e-flows. Durch die Kombination einer umfassenden Überprüfung mit einem praxisorientierten, lernenden Modellierungsansatz werden die wichtigsten Möglichkeiten, Herausforderungen und Einschränkungen bei der Anwendung von Optimierungsmodellen im Wassermanagement untersucht, mit dem Ziel, Entscheidungsprozesse an der Schnittstelle von Modellierung und Management zu verbessern.

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Publication list

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Author contributions

DEREPASKO ET AL. (2021), CHAPTER 2: DD designed and conducted the research and wrote the manuscript. MV, JG and AH developed the research idea and edited the manuscript.

DEREPASKO ET AL. (2021), CHAPTER 3: DD developed the optimization functions, ran the optimization model, analyzed the results, and wrote the manuscript. FJP and JB assisted with the definition of environmental flow requirements and the writing of the respective sections. MV developed the research idea, and MV, FJP, and JB edited the manuscript.

DEREPASKO ET AL. (2023), CHAPTER 4: DD developed the optimization functions, ran the optimization model, analyzed the results, and wrote the manuscript. FJP and JB assisted with the definition of environmental flow requirements and the writing of the respective sections. MV, FW, AH, FJP and JB developed the research idea and edited the manuscript.

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Table of contents

List of figures

List of tables

Thesis at a Glance

This thesis explores the role of optimization modeling in addressing water allocation problems and resources for environmental flows (e-flows) and its applicability to river management across various scales.

Paper 1

Aim: Investigate the stages of optimization problem development for water management from a scale-wise perspective, focusing on trade-off decisions linked with data availability and modeling and the implications of each choice.

Method: Literature review of multi-objective optimization studies that address water management problems considering environmental flows.

Conclusions: The proposed framework helps clarify the role of scale in water management and emphasizes the need for transparency. At the same time, it provides clear steps for defining the optimization problem and implementing the desired assessment scales.

Paper 2

Aim: Demonstrate how an optimization assessment can be integrated into the adaptive management cycle to effectively incorporate environmental flow requirements into water diversion management. The approach is designed to balance ecological conservation needs with human water demands.

Method: Multi-objective optimization (NSGA-III), hydrological scenarios, and e-flow requirements for three key biological groups within the case study area (Pas River segments).

Conclusions: Optimization assessments can facilitate the incorporation of e-flows into water management plans. Water management must take into account seasonal variations in water availability for diversion. The proposed methodology can be applied to other river basins; however, detailed monitoring and flexible thresholds are required.

Paper 3

Aim: Explore the application of the optimization approach for river water diversion at the basin scale under future climate and land use change scenarios to identify modeling options and management practices that best facilitate the implementation of adaptive management.

Method: Multi-objective optimization (NSGA-III), land use and climate scenarios (BAU and nature-based), and e-flow requirements for three Supporting ES within the case study area (Pas River basin, 500-m segment resolution).

Conclusions: Seasonal shifts and spatial heterogeneity in diversion volumes challenge future management of water diversion; adaptive management is better promoted by reviewing seasonal planning and setting local diversion targets.

The conclusion section examines the key challenges and limitations of the optimization approach and integrates a comprehensive review with practical insights for improving water management decision-making.

1. Introduction

As a renewable resource, the availability of water resources is highly variable in quantity and unevenly distributed across the landscape (Ciampittiello et al., 2024; Feng et al., 2017). Climatic and environmental factors, such as precipitation patterns and landscape features, significantly influence the timing of water flows and the location of natural reservoirs (Mittal et al., 2016; Sabater et al., 2023; Zolfagharpour et al., 2022). In an attempt to control this natural variability in supply and meet societal needs, water resource management and planning involve implementing various actions across the riverscape, including water impoundments, flow diversions, and flow regulation infrastructures or water pumping and transferring (A. C. Horne, Morris, Fowler, et al., 2017; Zeiringer et al., 2018). However, water availability is often limited in both time and space compared to human consumption demands while remaining essential for supporting ecological processes and sustaining species (Derepasko, Guillaume, et al., 2021; Docker & Johnson, 2017; Poff & Zimmerman, 2010).

In the context of rivers, the understanding that both river and adjacent land ecosystems need adequate water flows to function properly was formally recognized with the introduction of the concept of environmental flows (e-flows) during the "10th International River Symposium and International Environmental Flows Conference" that took place in 2007 in Brisbane (Australia) and ever since known as the "Brisbane Declaration". The concept of e-flows emphasizes the intricate connection between ecosystem processes and river flow dynamics, including elements like base flows, high flows, and water temperature. Recognizing these components is essential to maintaining ecosystem health and conservation. The most recent definition of e-flows (Arthington et al., 2018) states that e-flows correspond with "*the quantity, timing, and quality of water flows required to sustain freshwater and estuarine ecosystems and the human livelihoods and well-being that depend on these ecosystems.*"

The acknowledgment of e-flows importance also marks a significant milestone in river flow preservation and restoration efforts. It is key in shaping protection measures and policies for rivers and related water bodies, such as the European Water Framework Directive. This is particularly relevant for many rivers worldwide, which face intense exploitation to meet human demands. In fact, it is well established that heavy river regulation can cause various negative impacts on river ecosystems and habitats, threatening the survival of species and communities while disrupting ecosystem services that benefit society (Ekka et al., 2020; Nilsson & Berggren, 2000; Opperman et al., 2019). The most evident impacts of river regulation and water management in river basins stem from damming and impoundment infrastructure able to drastically alter flow regimes, though the full extent of these impacts is not fully understood (Brown et al., 2024; Olden & Naiman, 2010; Zargari et al., 2023). While damming significantly disrupts natural flow patterns, other perturbations like weirs, water abstraction through pumping, and flow diversion also affect ecosystem integrity by reducing flow magnitude and hampering peak flow events (Brown et al., 2024; McKay & King, 2006; Olden & Naiman, 2010; Yu et al., 2020; Zargari et al., 2023). These disturbances can interfere with the environmental cues that trigger phenological responses in certain species, as supported by evidence (Bunn & Arthington, 2002; Lytle & Poff, 2004).

Several approaches have been developed to capture the fundamental components of the relationship between river ecosystems and river flows, referred to in this thesis as environmental water requirements (sensu A. C. Horne, Webb, Stewardson, et al., 2017). Well-represented approaches in the literature are primarily based on hydrologic and hydraulic modeling of flow regimes and habitat range, ecological processes, phenological stages, and growth/richness indicators or indices (Webb, Arthington, et al., 2017). While no single approach is definitive, they all share the understanding that the presence of specific conditions is essential for sustaining the ecosystems (Poff et al., 2017). The most widely applied approaches for ecological conservation in rivers are based on two main concepts: the "natural flow regime" and the "designer flow." The former emphasizes the need to allow the river to flow according to its natural conditions (e.g., peak flows, low flows, and their timing), reducing the interference to a minimum (Poff et al., 1997). At the same time, the latter involves the artificial delivery of appropriate water volumes at specific times (frequency) to mimic the natural flow of the river but with the ultimate goal of achieving desired outcomes such as particular ecosystem services (Acreman et al., 2014). The "designer flow" approach is particularly suited for regulated and heavily regulated rivers, such as those impaired by dams or artificial impoundments.

In view of the urgent need for sustainable river water allocation, research has recently focused heavily on strategies for incorporating environmental flows (e-flows) into regulated river management decisions. However, despite their crucial role in promoting the well-being of both ecosystems and society, the practical application of this concept remains limited (Arthington et al., 2024). This gap is further compounded by the complex array of often conflicting objectives that water management must balance. Most river management efforts prioritize ensuring sufficient water for drinking, industrial use, and agriculture. Achieving these objectives demands decision-making across different scales and involves coordination across multiple levels of governance (Docker & Johnson, 2017; L. O’Donnell & E. Garrick, 2017). For instance, local governance includes municipalities' responsibilities to protect water diversions from river segments, while basin-scale governance offers a broader perspective on the watershed cycle, encompassing all institutions involved in water use and allocation.

To achieve these management objectives, different approaches are used to implement e-flows depending on the governance level (local, regional, or national). These include demand-based strategies, such as caps on water abstraction, and ecosystem-based strategies, such as allocating certain amounts of water to the environment (Docker & Johnson, 2017). Both strategies fall under the broader framework of Integrated Water Resource Management (IWRM), which marks a pivotal shift in water management history—from traditional methods to a more holistic approach that considers society, the economy, and ecosystems as interconnected components (Ibisch et al., 2016).

Nearly two decades have passed since adaptive water management emerged as a promising paradigm for sustainable water resource management, offering an alternative to the traditional IWRM approach (Pahl-Wostl, 2006; Webb, Watts, et al., 2017). At its core, it involves continuously monitoring the outcome of decisions and adjusting actions to better achieve desired goals, making it especially effective at managing uncertainties and changing environmental conditions. In this way, adaptive water management provides a flexible framework for sustainable water resource management that allows for adjustments and improvements in each management cycle. However, despite its promise, there is currently no clear guidance on how to integrate adaptive management into practical water management practices successfully (Webb, Watts, et al., 2017). Consequently, water managers must monitor outcomes closely to ensure set goals are pursued as expected, especially in relation to maintaining ecosystem functions and integrity while balancing the diverse water needs of multiple stakeholders. This underscores the importance of tools that support informed decision-making before implementation takes place and facilitate a sustainable balance among competing demands.

Among the plethora of decision support tools available to address river water resource management problems (Wardropper & Brookfield, 2022), optimization provides the technical structure for navigating complex and often conflicting objectives (Derepasko, Guillaume, et al., 2021; Horne et al., 2016; Horne et al., 2017) such as water supply for human consumption, agricultural irrigation, industrial use, and the protection of aquatic ecosystems. Unlike most decision support tools that focus on a single component or management goal, multi-objective optimization allows decision-makers to consider multiple criteria simultaneously, capturing the nuanced trade-offs between them. For example, maximizing water allocation for agriculture may conflict with the goal of preserving environmental flows essential for aquatic ecosystems. To address these challenges, multi-objective optimization generates a range of optimal solutions, known as the Pareto front. Each point on this front represents a scenario where improving one objective necessitates sacrificing another. Decision-makers can then assess these trade-offs to identify a solution that aligns with their priorities and overarching management goals.

One of the key strengths of the optimization approach is its flexibility, allowing the incorporation of data from different spatial and temporal scales. This adaptability makes it especially valuable for addressing environmental conservation challenges in river management. For example, during water scarcity, managers must balance limited resources while maintaining the ecological integrity of the river system. Multi-objective optimization models can simulate various scenarios, accounting for factors such as seasonal water availability, sector-specific demands, and ecosystem requirements. By offering a range of feasible allocation strategies, these models help decision-makers assess trade-offs and identify solutions that optimally balance competing needs.

This approach is beneficial when implementing management strategies in the context of climate change, where traditional methods based on historical data may no longer be reliable (Derepasko et al., 2023). By incorporating optimization into management frameworks, decision-makers can better navigate future uncertainties and make informed decisions that align immediate needs with long-term sustainability.

Optimization has been widely applied to managing water infrastructure, such as dams, reservoirs, and irrigation systems (Derepasko, Guillaume, et al., 2021). These infrastructures often serve multiple purposes, including flood control, hydropower generation, and water supply, each with distinct objectives. For example, a dam may be operated to maximize hydropower output while also ensuring sufficient flow downstream to support fish populations and aquatic ecosystems. Optimization models can be used to determine the ideal operational schedule for such infrastructure and balance these competing objectives. By simulating various operational strategies, these models can identify schedules that offer the best trade-offs between hydropower generation, flood risk reduction, and environmental sustainability.

In addition to their technical benefits, optimization assessments can enhance decision-making in river basin management by fostering transparency and stakeholder engagement. Defining objectives and evaluating trade-offs require input from diverse stakeholders, including government agencies, local communities, industry representatives, and environmental groups (Horne et al., 2016; Horne et al., 2017).

Optimization models can provide a structured framework for incorporating these varied perspectives, ensuring that all relevant interests are taken into account (Castelletti et al., 2008; Mayer & Muñoz-Hernandez, 2009; Nikoo et al., 2017).

By offering decision-makers a range of potential solutions rather than a single "ideal" outcome, these models encourage a more inclusive approach to river management. Stakeholders gain insight into how different priorities can be balanced and actively participate in discussions about which trade-offs are most acceptable. This inclusive process improves the quality of decisions and increases their legitimacy and acceptance among affected communities, leading to more sustainable and widely supported management outcomes (Whitley et al., 2024).

Although optimization assessments provide a flexible technical structure for tackling the complex and interconnected challenges of river basin management—allowing a comprehensive overview of the trade-offs associated with various management decisions and enabling the development of strategies that effectively balance competing demands—several research questions remain unresolved. This thesis explores gaps related to scale, model reproducibility, and practical support for adaptive management strategies. Addressing these issues is essential for developing reliable optimization assessments and improving water management practices, ultimately enhancing the resilience and sustainability of water resource management.

One of the primary challenges for water management research is the issue of scale. There is a significant lack of understanding of the scales at which water management problems should be addressed, leading to inconsistencies in the input and output data (Lovell et al., 2002). This inconsistency affects the accurate representation of real-world conditions in simulated models. For example, management decisions made at the local level may overlook broader regional or even global impacts. At the same time, optimization models developed at larger scales may fail to capture critical local nuances. A unified approach is necessary for scaling results and, consequently, for the reliability and applicability of models used to inform water management policies (Cilliers et al., 2013). To meet this challenge, it is crucial to analyze the impact of modeling decisions at the model scales to avoid trade-offs between modeling capability and management needs. This thesis addresses the issue of trade-offs in scale representability within optimization modeling for water resource management and contributes to supporting model accuracy and relevance, ultimately enabling more effective decision-making that better reflects the complexities of real-world water management scenarios.

Another critical gap in water management research is the lack of flexible, easy-to-apply models. The increasing complexity of environmental systems and the necessity for effective decision-making have highlighted the need for structured modeling frameworks that enhance models' comparability, transparency, and transferability. In water resources management, such frameworks are essential for developing robust and adaptable strategies; however, many models lack the technical structure to accommodate diverse data types and outputs tailored to specific management needs. This results in using various methodologies, assumptions, and datasets or customizing indicators to fit modeling needs. Such a lack of versatility complicates the comparison of results across studies, reducing their applicability in decision-making. Additionally, the absence of a standardized framework for optimization model development hinders the reproducibility of results and limits the adaptability of models to different contexts. Since optimization offers flexibility in problem formulation and can efficiently process information in formats relevant to water management, this thesis explores the suitability of optimization models for integrating environmental flows (e-flows) into management practices at different scales.

Lastly, a major challenge in water management research is identifying practical tools that enable the implementation of adaptive management strategies. While adaptive management is necessary for handling uncertain future environmental conditions (Williams & Brown, 2016), there is scarce evidence on how optimization approaches can facilitate its application. Optimization techniques, which focus on efficiently allocating resources and achieving specific objectives, have the potential to play a key role in adaptive management implementation by identifying optimal strategies under changing conditions. However, the integration of optimization methods into adaptive management practices has not yet been fully researched. To address this gap, future research must focus on developing and testing optimization frameworks that can be easily integrated into adaptive management processes. This thesis addresses this gap by extending the applicability of optimization models across different scales and analyzing the spatial and temporal information generated by these models to determine how they can best support adaptive management in the face of future environmental changes.

Overall, this thesis aims to contribute to innovation in water resource management by advancing knowledge and providing new insights into the applicability of optimization models to solving sustainability problems in water resource allocation. It focuses on critical challenges in water resource management, such as incorporating e-flows, solving scale issues, and supporting adaptive management strategies. To achieve this, the dissertation is organized around three core research questions:

1. *What are the implications of model development choices on spatial and temporal scales when optimization models are used to reconcile e-flows with human water needs?*

2. *How can optimization approaches mediate the incorporation of e-flows into water diversion management? How can the resulting information support the implementation of adaptive management?*

3. *How can optimization models for river water diversion at the basin scale take future environmental changes into account while ensuring essential ecosystem services?*

To address these questions, both innovative descriptive and experimental approaches were used. The descriptive approach consisted of a comprehensive review of studies that apply optimization in water management with a focus on environmental aspects to evaluate modeling decisions and their implications for spatial and temporal scales. The experimental component, based on a "learning by doing" method, was conducted at two spatial levels (river segment and river basin) and was critical for evaluating the opportunities and limitations of optimization models use in integrating environmental flows (e-flows) and evaluating their potential to support adaptive water management practices.

1.1 Thesis structure

The structure of the dissertation is organized as follows:

- ***Chapter 2*****:** lays the foundation of my research by providing a comprehensive literature review that addresses the **first research question** and aims to deepen the understanding of trade-offs involved in decision-making when applying optimization models for water management at different spatial and temporal scales. It introduces a framework that harmonizes all model-related decisions into practical steps for optimizing model development. This framework emphasizes the importance of moving from result-oriented approaches to holistic strategies focused on model perception and formulation. Additionally, the chapter outlines key considerations and presents a series of critical questions designed to support the problem perception and formulation stages. These elements are essential for ensuring transparency and robustness in model development, ultimately enhancing the effectiveness of optimization models in addressing complex water management challenges and setting the stage for the subsequent exploration of optimization models in real-world scenarios addressed in later chapters.

- ***Chapter 3:*** builds on the framework from Chapter 2 by partially addressing the **second research question** by exploring the role of optimization within an environmental management cycle. While optimization is used to solve resource allocation problems as part of an integrated resource management approach, this chapter shows its potential for effectively incorporating environmental flows into decision-making processes. The chapter builds on the findings of an optimization assessment conducted at various river water diversion locations within the Pas River basin in Northern Spain. It demonstrates how expert-based ecological requirements can be translated into model parameters to achieve specific diversion goals, ensuring that human needs and ecological health are addressed. The approach presented identifies the temporal scales at which significant trade-offs in water availability occur and provides valuable insights to guide management action. In addition, the chapter examines the challenges and limitations of the optimization approach and offers practical suggestions for overcoming common obstacles that arise during its implementation. In this way, the potential of optimization methods to support adaptive management practices is emphasized, ultimately promoting a more sustainable balance between water resource use and environmental conservation. The insights generated here directly inform the broader-scale applications discussed in Chapter 4, providing a critical bridge between localized analysis and basin-wide strategies.
- ***Chapter 4*:** expands on the **second research question** while addressing the **third research question**. It investigates the suitability of optimization models for identifying appropriate scales for implementing adaptive water management approaches, which aid water managers in reducing uncertainty in decision outcomes. Implementing these strategies at larger scales—e.g., at basin or multi-basin levels—is a major challenge. This chapter explores the use of optimization models to balance water diversion needs for human consumption with the provision of ecosystem services, considering future environmental scenarios, including climate and land use changes. It proposes an evolutionary optimization model to guide diversion management, specifically in the Pas River basin. By incorporating these future scenarios, the model helps identify critical areas or "hotspots" in the basin where ecological needs could be at risk over various time periods. In addition, this chapter explains the key elements of the modeling process and provides recommendations for improving model development and adopting adaptive management strategies by water managers. The results show how optimization can play a crucial role in addressing the complex challenges of water resource management, ultimately promoting a more sustainable balance between human demands and ecological preservation. The recommendations presented here for improving model

development and adopting adaptive strategies connect back to the foundational framework established in Chapter 2 and the practical insights generated in Chapter 3, forming a cohesive progression toward addressing complex water management challenges.

- ***Chapter 5*****:** summarizes the research conducted and the most important results in relation to each research question and topic covered, highlighting each chapter's contribution to advancing optimization modeling in water resource management. It reflects on the limitations encountered and identifies opportunities for future research, ensuring that the insights gained throughout the dissertation are both actionable and forward-looking.

2. *Considering scale within optimization procedures for water management decisions: Balancing environmental flows and human needs*


Environmental Modelling and Software

Considering scale within optimization procedures for water management decisions: Balancing environmental flows and human needs

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Analyzed studies for this review can be found in *Appendix A* attached to this thesis.

2.1 Summary (abstract)

A key issue in optimization model development is the selection of spatial and temporal scale representing the system. This chapter proposes a framework for reasoning about scale in this context, drawing on a review of studies applying multi-objective optimization for water management involving environmental flows. In the chapter it is suggested that scale is determined by the management problem, constrained by data availability, computational, and model capabilities. There is therefore an inherent trade-off between problem perception and available modelling capability, which can either be resolved by obtaining data needed or tailoring analysis to the data available. In the interest of fostering transparency in this trade-off process, this chapter hence outlines phases of model development, associated decisions, and available options, and scale implications of each decision. The problem perception phase collects system information about objectives, limiting conditions, and management options. The problem formulation phase collects and uses data, information, and methods about system structure and behaviour.

2.2 Introduction

Water management is challenged by socio-economic (e.g. rising demand, sectoral competition) and climate change pressures (e.g. droughts, extreme events) (EEA, 2017; Grizzetti et al., 2017; Tonkin et al., 2019) threatening water security (Kennen et al., 2018) and river biodiversity (Vörösmarty et al., 2010). Despite increasing awareness of river ecosystems' needs (Angela H Arthington et al., 2018), water allocation goals typically still aim "to provide water to people when and where they most need it and not when and where it would naturally be available" (Daniell & Barreteau, 2014). However, addressing the challenges of climate change and increasing demand will require a range of strategic actions, including those that directly protect and restore the environment (Liu et al., 2016; Pittock & Lankford, 2010; Salik et al., 2016; Thompson et al., 2014). Failing to adequately incorporate ecosystem values and underestimating the potential cross-scale impacts of water use and climate change on freshwater ecosystems (McCluney et al., 2014) fails to acknowledge the benefits that freshwater systems generate for the wider community (Richter, 2009).

The implementation of environmental flows is one action that is already applied (A. C. Horne, O'Donnell, & Tharme, 2017; King et al., 2015; Le Quesne et al., 2010; Mendoza & Martins, 2006; N. L. Poff et al., 2010) to better protect freshwater and related ecosystems from modifications caused by river regulation (e.g. dams, weirs, diversion channels) (Arthington, 2012; N. L. Poff et al., 1997) and high-intensity use (EEA, 2012). The approach to implementing environmental flows and the accompanying water management decisions varies according to governance level, spatial extent and temporal scale of the desired outcome: broad-scale long term environmental flows (e-flows) management typically employs a 'top-down' approach by imposing limits to additional hydrological alteration (e.g. caps on water abstraction, license conditions for water users, environmental water rights, see Horne et al., (2018), whereas a 'bottom-up' strategy (e.g. conditions on storage operators, environmental reserve established legally) that considers ecologically-relevant components of the flow regime and their ranges is implemented at finer scales and generally prioritizes short term effects (Gopal, 2016; A. C. Horne, Webb, Stewardson, et al., 2017; Pahl-Wostl, Arthington, et al., 2013). Current incorporation of e-flows within integrated water resource management (IWRM) expresses environmental water requirements as quantity, quality and timing of water flows, in the short term at point-scale to limit impact propagation towards broader spatial scales in the long term (Vörösmarty et al., 2013; Evers, 2016; Angela H. Arthington et al., 2018). As a consequence, water governance seeks to implement enhanced management and infrastructure systems that can regulate river flow at multiple spatial and/or temporal levels (Daniell & Barreteau, 2014; Stewardson et al., 2017) in the light of changing consumptive water needs.

Scale-specific investigation tools are often used to inform successful river management (Volk et al., 2008). Case study-level applications show that some management problems envisage several objectives and hence multi-objective optimization can be used to address water management needs at different spatial scales, such as hydropower facility, reservoir, reach, sub-basin and basin and different temporal horizons (e.g. Shang, 2015; Yin et al., 2015; Fallah-Mehdipour, Bozorg-Haddad and Loáiciga, 2018). The optimization of a set of desired objectives related to water abstraction or release (e.g. species survival, hydropower production, domestic supply, irrigation) seeks to find optimal solutions. These solutions are searched across a range of criteria that allow the identification of trade-offs and synergies, and, as a result, the definition of compromises among conflicting goals (Cord et al., 2017; Gunantara, 2018; A. Horne et al., 2016). The opportunity to explore compromise solutions might better support decision-making processes than single-objective modelling, as it has been shown in other resource allocation problems (e.g. (Lautenbach et al., 2013; Kaya et al., 2016; Kaim, Cord and Volk, 2018).

However, modelling these decisions in water management is made challenging by the fragmentation and hierarchy of hydrological scales (Moss & Newig, 2010). A key obstacle is related to the consideration of the different scale-specific hydrological and ecological characteristics and processes (P. M. Davies et al., 2014; Thorp, 2014; Volk & Ewert, 2011). Indeed, the effective representation of connections (e.g. ecological, hydrological and geomorphological) on each temporal and spatial scale of the river network remains a core challenge in e-flow assessments (N. L. Poff et al., 2017). Another problem is related to the reference hydrological scales used in the classification of river spatial extent. The spatial mismatch between physical and socio-political boundaries poses a challenge for the definition and implementation of management objectives (Daniell & Barreteau, 2014; Moss & Newig, 2010; Opperman et al., 2018; van den Belt & Blake, 2015); Lastly, chosen e-flow parameters can be employed for studies at small scales and can show effects in the short term (e.g. population size), but can also be ecologically relevant for wider areas (e.g. basin-scale) and support processes that manifest at longer temporal scales (e.g. nutrient cycling) (N. L. Poff et al., 2017). This requires the consideration of a range of flow events (e.g. pulses, 30-day minimum flow) and diverse processes (e.g. water production, sediment delivery and vegetation dynamics, ecological stages, land cover influence) (Gurnell et al., 2016; Opperman et al., 2018).

In this paper, we present a framework that describes the conceptual and operational steps of optimization model development to support e-flows and the related spatial and temporal scale considerations. The framework draws on a review of the state-of-art in this field of water research. Clarity about the role of scale improves our ability to model across scales and as a consequence, provide more reliable predictions of decision outcomes at the scales of interest.

The chapter first introduces water management decisions and their translation into optimization models (see Box 1 for the definition of terms) and provides the outline of the proposed framework showing the stages of optimization problem development (i.e. problem perception phase and problem formulation phase) (Section 2.3 of this paper). The framework, mapping the scale-related decisions and options linked to each development phase, is further described with reference to results from the review of selected studies in Section 2.5 of this paper. Section 2.6 discusses the need for clarity of problem definition, strategies to implement desired assessment scales, and explicit discussion of trade-offs in problem development. Lastly, in Section 2.7 we provide recommendations to foster transparency throughout the optimization problem development phases.

Box 1. **Definition of terms**	
Environmental flow	The quantity, timing, and quality of freshwater flows and levels necessary to sustain aquatic ecosystems which, in turn, support human cultures, economies, sustainable livelihoods, and well-being (Angela H. Arthington et al., 2018).
Management objective	Specific statement about the intents of the water management approach (e.g. in relation to ecosystem services, processes and components) as a result of engagement between multiple stakeholders and managers. In the case flow management it relates to water allocation for environmental purposes. (adapted from Horne, Konrad, et al., 2017)
Optimization objective	Function to be either maximized or minimized, corresponding with 'outcomes of interest' of the optimization problem. Depending on the problem formulation, optimization problem constraints can substitute/complement objectives. (adapted from Maier et al., 2019)
Management decision	Mechanism through which a management objective is achieved (e.g. control of diversion and release, flow alteration reduction). High-level management decisions are tied to larger scales (e.g. provided through planning or regulatory instruments) while implementation decisions reflect management choices for periodic objectives at finer spatial and temporal scales. (adapted from Horne et al., 2018)
Optimization decision variable	Input parameter of the optimization problem that is measurable and controllable (e.g. reservoir water level, release timing, energy production), providing a quantitative representation of a management decision (adapted from Coello, Lamont and Veldhuizen, 2007).
Problem perception phase	The stage consisting of the consideration and interpretation of all the factors and processes (i.e. spatial, temporal, environmental and operational) involved with the implementation of the considered management decision (adapted from Beven, 2012).
Problem formulation phase	Encompasses all the actions related to the translation and modelling of the perceived problem into functions (i.e. objectives and constraints). Involves also the consideration of data needs to appropriately represent the area of interest of the water management problem (adapted from Maier et al., 2014, 2019).
Optimization problem	Or optimization model is the formulation of the management problem within a simulation/modelling context. This is the mathematical formulation of the water management problem.
Optimization framework	Structured set of steps and considerations used for the formulation of an optimization problem. In this study it is applied in support of optimization problem definition for environmental water management, highlighting the role of each step in defining the resulting scale of the assessment.
Optimization scenario	Captures a degree of variability in the optimisation problem to reproduce system behaviour under different possible circumstances (e.g. operational, climatic, and hydrological). The concept of an optimization scenario is intended to capture variations of the decision problem formulation, which can include alternative climate projections or decision variables, and their resulting outcomes.
Infrastructure operation	The time steps of the scheduling (frequency) of infrastructure operations' set.
Planning horizon	The timeframe upon which management decisions are taken. From a water management perspective, it usually corresponds with one management cycle and is linked with the previous

	(management objectives) and the following (monitoring outcomes) management cycles (adapted from (Horne et al., 2018). From an infrastructure management perspective, can also be associated with the frequency of updating an operational management plan.
Spatial scale	The spatial bounds of the events and processes considered in the optimization problem (in relation to a management problem) (Iwanaga et al., 2021). Common spatial scales used in water management related to hydrological units and flow altering structures (see Table 2 and Figure 4).
Temporal scale	The temporal horizons of the events and processes of the considered optimization problem (in relation to a management problem) (Iwanaga et al., 2021). Levels of temporal scale (e.g. days, months, years) can relate to the temporal resolution of hydrological data (adapted from Daniell and Barreteau, 2014). In water management optimization it can also refer both to the infrastructure operation cycle time steps and the planning horizon time window.

2.3 A framework for incorporating scale within optimization modelling to support e-flows water management decisions

An optimization approach offers the opportunity to explore compromise solutions to support decisions about scarce water resources (A. Horne et al., 2016). It can be used to support environmental water management decisions while meeting conflicting water use objectives (e.g. hydropower generation, domestic supply, industrial supply, irrigation water). Environmental water objectives drive management actions that can be implemented at broader (e.g. control of diversion) or finer target scales (e.g. need to control reservoir releases). The timeframe of implementation also varies based on the management decision.

Water resources management, and in particular e-flows, sit within an adaptive management framework that reflects these different temporal and spatial scales (Webb, Watts, et al., 2017). The selection of objectives and high-level policy decisions are made at a longer time scale and often for larger catchments or whole basins (Horne, Webb, et al., 2017). However, implementation decisions are made at a shorter time scale and often for a specific site or location. Optimization to support these decisions therefore also lends itself to be framed within an adaptive management framework, providing the structure and technical capacity to support trade-offs and decision making at different scales (Figure 1). Each stage of the adaptive management cycle has its own technical challenges. Similarly, the translation of management decisions into an optimization procedure needs to consider a range of factors to ensure the context and system is realistically represented. Table 1 uses a number of examples to demonstrate the importance of the type of management approach being considered (the columns in Table 1) for informing the approach to optimization model development. For instance, the decision to set a cap on abstraction can be tied to optimization at basin scale considering an annual or seasonal time frame; the optimization of release timing (at seasonal, monthly or daily scale) in response to the need to meet downstream ecological needs/target ecological indicators will be preferred for management decisions at smaller spatial scales (e.g. reaches or sub-basins) to match species ecological response timeframes and local hydrological conditions; at sub-daily scale it could be applied to reduce hydropeaking impacts at target locations. The specific decision context dictates the target scales. However, translation of real-world management problems into a modelling framework presents some inherent challenges, either related to data availability, modelling or computational ability. The water management analyst dealing with optimization model development hence faces a range of trade-offs in model representation, in particular linked with choices of scale associated with the targeted problem and resulting modelled representation. Any optimization model development procedure to support e-flows decisions and water resource management will need to explicitly consider the implication and magnitude of these trade-offs for the spatial and temporal scales of the assessment, to foster transparency and understandability.

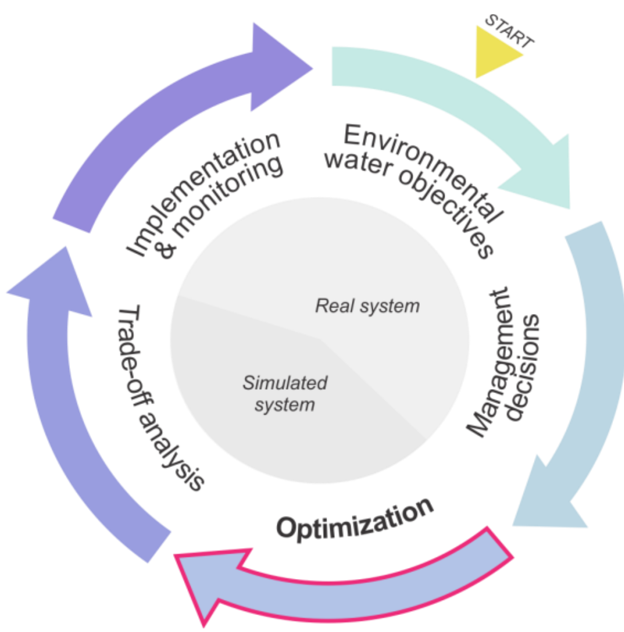

Figure 1 **Position of the optimization process within the adaptive water management framework** (yellow triangle indicates the starting point for each management cycle)

Table 1 **Overview of water management decisions underpinning optimization procedure definition**. The table shows for every decision examples of the corresponding approach undertaken during optimization procedure development and the temporal and spatial scales of the corresponding approach undertaken during optimization procedure development and the temporal and spatial scales of implementation. Note that in some cases also mixed approaches can be used.

Management Decisions	**Control of diversion**	**Management planning**	**Control of releases**	**Impacts reduction**
Examples	Setting a cap on maximum diversion	Incorporation of minimum environmental flow regimes into existing or new management plan	Optimization of reservoir release timing	Hydropeaking impacts reduction
Description	Specification of the maximum volume of diverted water that would allow maintaining the river regime at targeted levels	Incorporation of e-flow regimes into water management plan while meeting societal needs	Release timing adjustment to meet ecological water demand needs and/or reduce natural water flow alteration	Limitation of excessive water volume discharge downstream of the reservoir to mitigate adverse human and ecological effects
Type and frequency of flow modification	• Definition of specific % limits on the degree of allowable natural flow alteration • Definition of period-specific thresholds on river volume diversion	• Testing the feasibility of incorporating different minimum e-flows regimes into current schemes against a range of climatic or supply reliability scenarios	• Minimization of the deviation from reservoir storage and rule curves • Prescription of releases to meet specific downstream ecological needs • Reduction of the gap between natural flow and outflows	• Operational scheme synchronization of peak water volume releases with natural flooding or pulses
Targeted temporal scale	• Seasonal • Annual	• Annual	• Daily • Monthly	• Monthly • Seasonal
Targeted spatial scale	• Basin	• Basin	• Point scale (reservoir) • Multi-reservoir	• Basin • Sub-basin
Targeted ecological effects	• Long term effects at the ecosystem scale	• Long term effects at the ecosystem scale	• Population structure and size • Non-native species reduction	• Native community composition • Sediment budget
Comments	Participatory and/or multi-disciplinary workshops needed to define appropriate flow alteration	Would need the definition of plausible minimum e-flow regimes	Needs the definition of appropriate ecological indicators	Especially meaningful for large infrastructure

A general optimization process (showed in Figure 2, left-hand side) first involves problem identification (or contextualization) and subsequently, requires input parameters definition and optimization environment creation (Maier et al., 2014). As a first step, the system domain is defined by the water management problem and decisions which underpin the relevant objectives, constraints, and scenarios of the targeted spatial and temporal scales of assessment (Figure 2, right-hand side). Once defined, the system characteristics, hydrological data, and other relevant information (e.g. ecological) are gathered to meet the requirements for representation at the targeted scales. Given that optimization assessments need to inform a decision making process (hence the output), the final scales of the assessment should appropriately match decision conditions and scales. Trade-offs in system representation arise when moving from problem perception phase to problem formulation phase as a consequence (see Section 2.5). Specifically, the trade-off can be resolved either by seeking additional information required to implement or by altering the problem perception to suit the information available. The precise process of achieving a trade-off is not well understood, and a variety of approaches and intermediate solutions may be possible (Fu et al., 2015). Figure 2, together with Tables 3-7 in Section 2.5, provide a framework in support of model development in the interest of fostering transparency in the trade-off process around decision making and option selection during these two distinct phases of optimization model development.

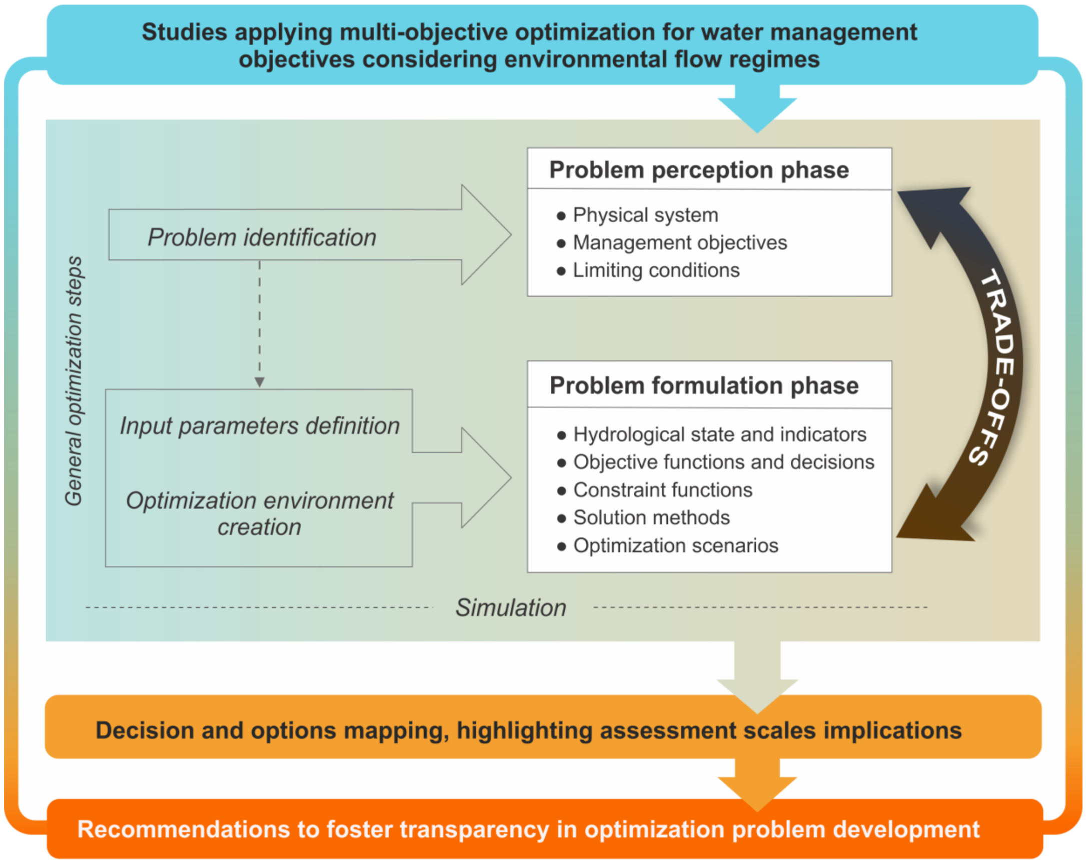

Figure 2 **Conceptualisation of optimization process, as adopted in this analysis**. Scheme of a stepwise general optimization procedure (left-hand side); Structure of the analysis applied in this paper (right-hand side): analysis of optimization procedure development for water management problems focused on two distinct phases, problem perception phase and problem formulation phase

2.4 Data collection

The proposed framework (see Tables 3-7 in Section 2.5) for assessing scale within optimization modelling to support e-flows was developed through a detailed review of existing literature that applied optimization in this context. We analysed existing literature and the options presented for each modelling element in the framework (Figure 2), the targeted spatial and temporal scales, and the assets considered.

Data collection for the analysis was carried out by performing a literature search. The focus was set on studies that applied optimisation of water diversion or impoundment to environmental water management decisions while meeting human water needs at different spatial and temporal scales. Keyword combinations were used in the 'Web of Science' search engine (i.e. multi-objective optimization, multi-criteria optimization, optimization, environmental flows, e-flows) to generate the initial set of literature. The collected studies were filtered for water management and the final selection was based on the criterion that they had to address both ecological and societal water use. Studies were excluded mainly due to their character (e.g. framework, review) or because of the study objective (e.g. focused on land use). In a few cases, studies focusing only on a single objective function but considering both needs (i.e. ecological and anthropogenic) have been included in the analysis, due to their compliance with the aim of the review and to stimulate discussion. A final collection of 27 case studies applying optimization procedures at different targeted scales was analysed (see references in Table A1, in the Annex). The overall objective of the review process was to highlight existing decisions and options for each phase of model development and to feed into the guidance framework for scale implications of modelling decisions.

2.4.1 Definitions of scales in multi-objective optimization procedures for water management

Defining comprehensible scales and their consistent use is still a key issue in systems modelling (Iwanaga et al., 2021). The interdisciplinary nature of water resource management exacerbates this with different spatial and temporal boundaries related to the multiple aspects of water management (i.e. administrative, hydrologic, management, etc.) (Daniell & Barreteau, 2014; Gleeson & Paszkowski, 2014; Moss & Newig, 2010). As policy decisions can be defined based on model outputs, (Dabiri and Blaschke, 2019) distinguished between the policy and the modelling scales, and associated the latter with the "dimension at which the data is acquired or derived" and in strict connection with the mathematical expression; similarly, (Moss and Newig, 2010) distinguish the 'hydrological' and the 'political' scales as central dimensions for water management modelling. On the other hand, in landscape ecology, scales are usually associated with patch extent or duration and grain or resolution (Withers & Meentemeyer, 1999). Most studies related to socio-environmental modelling consider the extent and resolution to define spatial and temporal scales (Dabiri & Blaschke, 2019; Daniell & Barreteau, 2014; Gleeson & Paszkowski, 2014; Iwanaga et al., 2021; Moss & Newig, 2010). Both spatial and temporal scale resolution is linked with data: grain size or cell size represent the smallest features of the spatial scale (particularly if the modelling is spatially-explicit); while time-steps represent the levels of the temporal scale (e.g. hours, days). In this study, we consider these notions to define spatial and temporal scales for optimization modelling for water management (see Box 1).

Studies optimizing water management usually indicate the targeted area for the assessment. Table 2 shows the spatial scale definitions we retrieved from the analysed studies. For each we provided a description of the features of the considered scales. While these definitions were linked with the focused assessment area and thus presumably belong to the 'problem perception phase', we found an ambiguity in the use of the terms sub-basin, multi-reach and river section scale. In fact they seem to be used interchangeably and possibly relate to modeller's understanding of the system. However, this seems to be in accordance with the conclusions of (Gleeson and Paszkowski, 2014) who found that hydrological scales definitions are not used consistently among researchers. We use the definitions provided in Table 2 as mean of comparison throughout the paper.

Table 2 **Spatial scales used for optimization modelling applied to water**Figure 3 **Position of the optimization process within the adaptive water management framework** (yellow triangle indicates the starting point for each management cycle) **management.** We identified a set of recurrent definitions in the reviewed studies that refer to the targeted assessment areas and their meaning.

Definition	Description
Multi-basin	A series of adjacent basins.
Basin	The hydrological delimitation of the river domain, formally defined as the land area that collects the rain or snow water generating the flow and the river network. Can refer to the whole river network.
Sub-basin	An area of the river network (as part of a defined basin) that encompasses a series of adjacent and interconnected reaches. The latter can eventually merge with a bigger tributary.
Multi-reach	Several reach sections of the same river. It can encompass multiple tributaries throughout the river network. Depending on the number of considered reaches (and their proximity) this may be similar to a sub-basin scale or river section.
Reach	A section of the river that presents similar hydrological characteristics (e.g. discharge, depth). Usually it represents short river portions or small tributaries. Sometimes it can be associated with the river section scale.
River section	A portion of the river network of variable length that is arbitrarily defined by the user. It could encompass the portion of the river stretch included two key points (e.g. gauging stations, dam, and connection to another tributary).
Reservoir	Body of water artificially impounded by a dam, commonly with potential for controlled releases
Infrastructure	Human assets linked to the river flow (e.g. dams, reservoirs, weirs) that are used to supply water or energy for human consumption, regulate the floods or provide navigation.
Multi-infrastructure	A series of infrastructure located in different sites of the river network. Can refer to a number of in-series infrastructures (i.e. consecutively positioned on the same river section) or on multiple reaches.

2.5 Lessons from the literature: scales in multi-objective optimization procedures for water management

Environmental water management problems in regulated rivers can represent different issues related to the delivery of e-flows. For example, e-flows can be incorporated into an existing operational plan or infrastructure operation can be modified to reduce flow alteration (see Table 1 in Section 2.3). Modelling these management problems requires the definition of the targeted area and the available information during the 'problem perception phase' (Section 2.5.1) and the selection of the modelling approach in the 'problem formulation phase' (Section 2.5.2). Both phases are exposed to scale issues related with the data resolution, the temporal horizon for the operation plan and spatial boundaries of the system. Box 1 and Box 2 describe two example case studies. In the following sections, we elaborate on the framework by drawing on the considered literature to discuss the different stages within each phase with the aim of understanding the trade-offs between the management problem scales and the modelling problem scales.

Box 1. **Case study: the Luis L. Leon reservoir (Big Bend reach)** (Porse et al., 2015)	
Management problem (perception phase)	Incorporation of environmental flow requirements into reservoir operation. Respect of supply requirements subject to international treaty. Demonstrating that environmental flow allocations can be increased.
Considered system:	River segment delimited by two reservoirs, with releases from one reservoir, tributary inflows, water extractions, flow at multiple gauges, inflows to second reservoir. Existing environmental flow requirements for basin and longer river segments could also have been used.
Operational timescale	Monthly reservoir releases, flows, and water extractions
Planning horizon	Multi-year; treaty works on 5 year cycles not explicitly modelled here.
E-flow approach:	Prescribed hydrograph describing environmental flows monthly targets (base-flows, high flows and small/large floods developed from statistical analysis of hydrological record), scaled to vary total environmental flow volumes
Optimization problem (formulation phase)	Decision variables: monthly reservoir releases in two reservoirs Objectives: Minimization of total environmental flow deficits for all months Constraints: monthly mass balance continuity equations, total flow and minimum storage requirements approximating treaty stipulations; limits to storage and change in storage between months for operational constraints.
Input data	Flow record, water demands data, infrastructure operations from a prior water allocation model (1969 to 2009), e-flow requirements (literature) for BB reach
Optimisation approach	Linear programming
Scenarios	Water availability scenarios – total environmental flow used to scale monthly environmental flow targets: (a) 600; (b) 800; (c) 1000; (d) 1100; and (e) 1200 mcm.
Our comments on spatial scale	Flows at one gauge assumed to be representative of environmental flow requirements along entire river section. Full implementation of treaty requirements and trade-offs with upstream and downstream EF requirements would need expansion of spatial scale. River segment focus demonstrates feasibility of local changes all else being equal.
Our comments on temporal scale	Multi-year management cycles are not explicitly modeled (management-implementation scale mismatch). Monthly rather than daily time step may not capture shorter term breaches of operational constraints. Expression of environmental flow as monthly average discharge conditions may not capture requirements at shorter timescales. Analysis assumed to make convincing case despite simplifications.

Box 2. **Case study: the Peishih Creek** (Shiau & Wu, 2013)	
Management problem (perception phase)	Plan release environmental water for three interconnected reaches (subject to various degree of hydrological alteration) while ensuring domestic water supply and hydropower production
Considered system:	Reservoir connected to river section (with weir diversion), performance measured for 1, 2 and all 3 reaches
Operational timescale	Hourly flows, with release decisions spread through the day, and flow indices aggregated to multiple scales
Planning horizon	Multi-year
E-flow approach:	Measurement of natural flow alteration through 5 hydrological indices: RBF*, daily flow, monthly flow, annual 7-day minimum flow and 5-year floods.
Optimization problem (formulation phase)	Decision variables (15): 2 environmental flow proportions, 3 three-period release parameters, 3 hedging coefficients, and 7 compelling release parameters. Objectives: TOPSIS (technique for order preference by similarity to ideal solution) transforms multi-objective problem into single objective Reservoir performance objectives: minimization of long term shortage ratio, mean annual deficit duration, maximum 1-day shortage ratio; maximization of mean annual hydropower production, flood attenuation. Environmental water objectives: minimization of difference to pre-impact RBF, difference to daily hydrograph, difference to pre-impact monthly flow, difference to pre-impact annual 7-day minimum flow, difference to pre-impact 5-year floods. Constraints: only limits on decision variables. Routing model used to simulate flow.
Input data	Flow record (1998 to 2008) of reservoir inflows and Nanshih Creek's river flow.
Optimisation approach	Genetic algorithm in simulation-optimization framework
Scenarios	Operation scenarios: (a) 1-reach scenario with 10 objectives, (b) 2-reach scenario with 15 objectives, (c) 3-reach scenario with 20 objectives.
Output	Hourly reservoir releases; weir diversion volumes at Nanshih Creek, and post-impact flows at the three study reaches.
Our comments on spatial scale	Exploration of multiple scales; bottom of system defined implicitly in figures as junction with larger watercourse. Reaches defined based on nature of hydrological alteration provides natural segmentation while recognizing that ecosystem response has not been addressed. Selection of reaches significantly affected results.
Our comments on temporal scale	Inclusion of hydrological alteration at multiple scales as objectives, then reduced to single objective by comparison to ideal point such that trade-offs are not explicitly explored. The planning horizon of infrastructure operations is not clear, especially in relation to projected demand magnitude, as the only available information is the data timeframe (10 years).
Notes: *Richards-Baker flashiness index (RBF);	

2.5.1 Problem perception phase

Physical system

The concept of 'system' is expanded in water management to include the geographical, temporal and the socio-economic setting of the applied optimization procedure. The physical system can be defined in terms of the spatial area, including that involved in the generation of the water flow and the structural limits of the studied facility (e.g. a reservoir), and the temporal window of effect. Figure 3 illustrates systematically the spatial and temporal scales that interest water management problems and highlights some of the major factors that have scale implications, based on the reviewed papers. The definition of spatial area and temporal window of effect provides the physical-temporal target reference for the following problem formulation phase. Here, we split the decision related to physical system perception into multiple decisions related to the flow alteration infrastructure: the type and number of flow altering infrastructures, and its operations; the definition of environmental assets; and, the definition of the management horizon (see Table 3). Temporal scales tend to be fairly well-defined by flow alteration type (impoundment, diversions), the management horizon, and the points of interest (and hence spatial scale). Points of interest include flow altering infrastructure, which affects how that infrastructure is operated, as well as e-flow target locations (e.g. river reaches, environmental assets).

Optimization assessments are developed to reflect operational schemes of impoundment and diversion structures at a range of management horizons. Considering all the resulting options related to the planning horizon, the selected facilities and the spatial range of their impact inevitably leads to a series of possible context-infrastructure combinations. In this case, system conceptualization benefits from the visualization of connections between assets, especially in large highly regulated river systems, as in transboundary river basins (e.g. Martin et al., 2017; Schlüter et al., 2005). Such visualization enables the definition of points where water movement is related to different causes (e.g. supply, inflow, storage), expressed as point sources (e.g. tributaries), releasing points (e.g. dams, hydraulic structures), and gauging stations facilitating optimization procedure development.

The wide variety of possible network configurations means that the targeted hydrological scale can range spatially from reach or river sections (e.g. Mullick, Babel and Perret, 2013; Fleifle et al., 2014) to sub-basins and multi-reach systems (e.g. Xevi and Khan, 2005; Shiau and Wu, 2013) or an entire basin (e.g. Suen and Eheart, 2006; Shiau and Chou, 2016). The consideration of the number of assets and their location as well as the scale of effect influences the final size of the spatial domain. Figure 4 illustrates the different targeted assessment scales as emerged from the analysed studies.

A key challenge in the problem formulation phase is articulating the target for environmental outcomes. Environmental assets can include not only in-river values but also attributes of wetlands and floodplains (e.g. Szemis, Maier and Dandy, 2012, 2014; Szemis, Dandy and Maier, 2013). The environmental objective can be represented in several ways, for example as the provision of habitat or as the provision of ecosystem services. This clear articulation of environmental outcomes (as opposed to hydrological indicators) has been more evident in Australian case studies and management contexts. It is acknowledged that this need to define a-priori the targeted environmental assets during the optimization model procedure is a significant challenge, however, it represents good practice for system definition.

Lastly, management context decisions relate to operational horizon or release schedules. Infrastructure operational horizon can be tailored both at sub-daily or daily scale as this supports the identification of the best option based on hourly flows or how much water is to be allocated. The management horizon should also be consistent with the frequency of need to update the management plan. We identified studies using management horizon that were monthly, seasonal, single, and multi-year. When targeting single or multi-year management horizon, water releases are assessed for different single years, differentiating by wet, normal, dry, allowing to implement the best releases or abstraction operations based on the yearly hydrological conditions type (e.g. Steinschneider et al., 2014; Chen and Olden, 2017; Dai et al., 2017; Lewis and Randall, 2017). Policy testing could require the definition of multiple alternative management horizons. Conception of alternative legislative contexts can consider the prioritization of different combinations of objectives (e.g. Shiau and Wu, 2013).

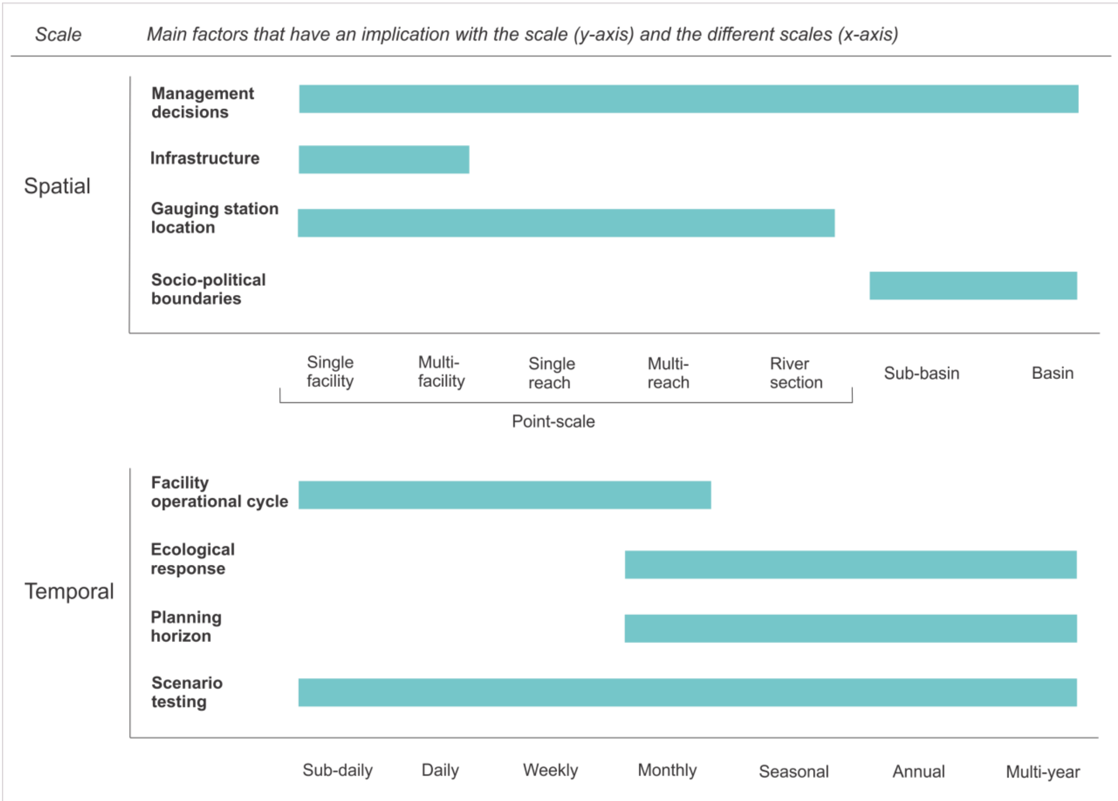

Figure 3 **Temporal and spatial scales that define water management optimization problems.** This figure is based on the results of our analysis. It illustrates the different spatial and temporal scales in relation to certain factors which challenge optimization procedure development by means of decision and option selection complexity, and definition of the resulting system boundaries.

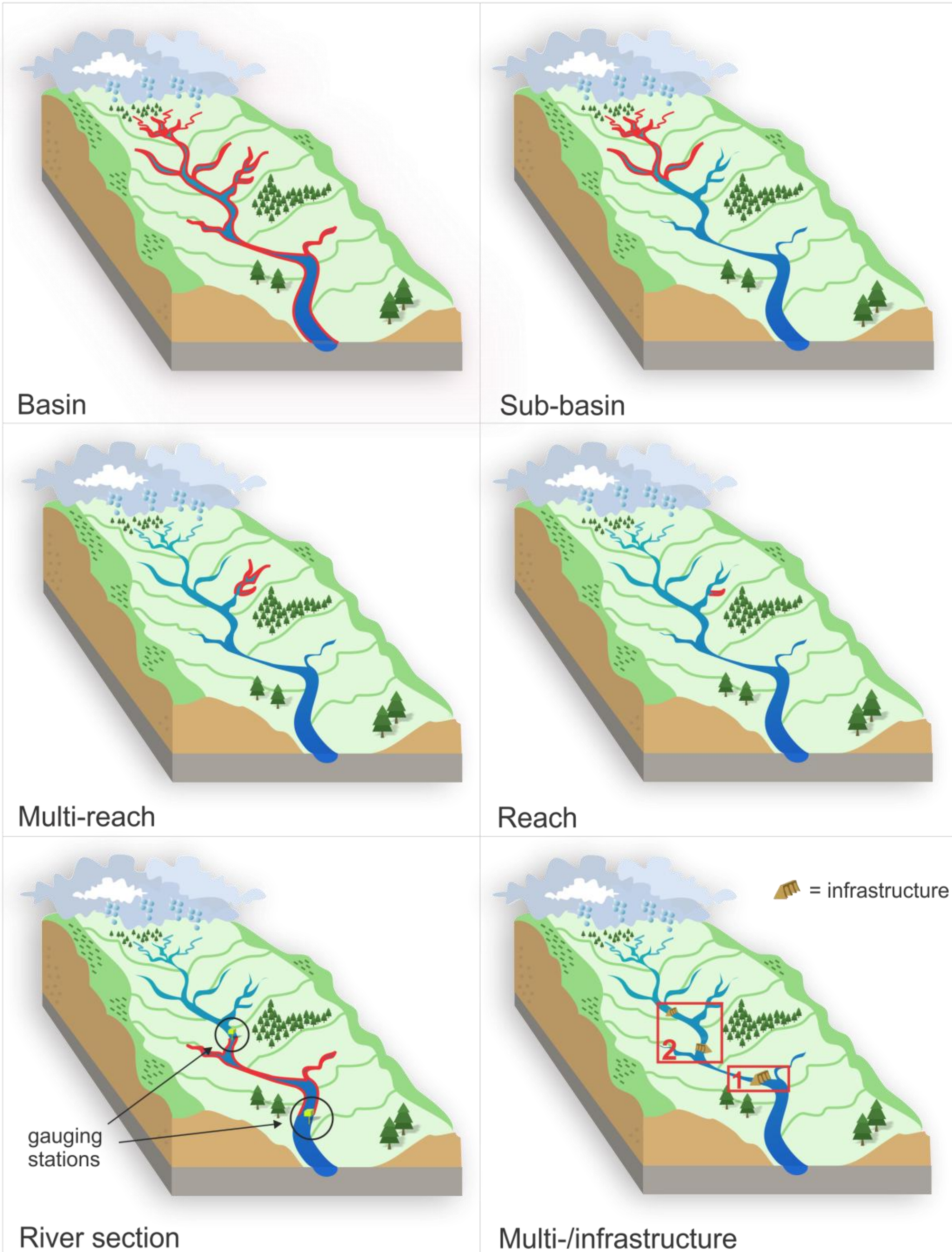

Figure 4 **Illustration of different spatial scales considered in the reviewed studies.** For description see Table 2.

Table 3 **Framework 1/5.** Summary of the decisions and options, and related scale considerations for the 'Physical system' step during the 'Problem perception phase'.

Assessment phase	**Modelling element**	**Decision**	**Description**	**Related options**	**Spatial scale relation**	**Temporal scale relation**	**Relationships between options**
Problem perception phase	*Physical system*	Definition of flow alteration type	Definition of the flow altering infrastructures that belong to the considered regulative unit and consideration of their functioning	• Diversion • Impoundment	Need to consider the scale of effect and nature of flow alteration	Need to consider infrastructure operations	This step influences the incorporation of the management decision
		Definition of the number of flow altering infrastructures	Consideration of all the assets in the target unit	• Single-infrastructure • Multi-infrastructure • Single with mixed-use (e.g. impoundment with power generation)	Affects the scale of representation of the infrastructure network	Need to consider operative conditions (schemes) of all the assets. Hence could affect the final timeframe.	This step influences also the choice of the solution approach (number of decision variables or objectives). Requires awareness of possible influences between assets
		Definition of infrastructure operations	Consideration of the operative scheme of the selected infrastructure	• Monthly • Daily • Sub-daily	Spatial scale of effect is influenced by timeframe	This relates to the timeframe of the operation cycle, involving both flow alteration type and configuration of infrastructure assets	Option selection could affect the choice of the scenario

		Definition of environmental assets	Consideration of the type and characteristics of the targeted environmental assets and their location	• Ecosystem type (e.g. wetlands) • Ecosystem services (e.g. habitat provisioning areas)	Affects the scale of representation	Needs to consider infrastructure operations and flow alteration type	This step could influence scenario definition
		Definition of the management horizon	Consideration of the frequency of needs to update the management plan	• Monthly • Seasonal • Annual • Intra-annual	Spatial scale of effect is influenced by management timeframe	Affected by uncertainty in driving conditions and system knowledge, as well as the ability to adapt plans over time	This step could influence the type of scenarios and hence trade-offs analysis

Management objectives

The definition of optimization objectives reflects a range of management objectives or goals that can then be assessed for compromises in water allocations or other water release variables (see Table 4). There is a range of different formulations of system objectives, e.g. maximization satisfaction of consumptive demand (or minimization of shortfalls), optimization of structural performance, the maximization of economic benefit, or minimization of the hydrological disturbance. The way the objectives are expressed is linked to the spatial extent but can reflect end-user needs. For example, the need for controlling floods is more pressing at the basin scale and can be managed by considering the difference between inflows and outflows (e.g. Porse, Sandoval-Solis and Lane, 2015; Shiau and Chou, 2016).

Studies aiming at maximizing water supply seek to ensure water supply maintenance over time by adjusting to flow fluctuation, rather than aiming to abstract the greatest possible amount of water at a single time-step. The operational scheme of the facility (i.e. impoundment or diversion) affects the approach for the definition of supply reliability. Targeted reservoir releases for downstream ecological needs are sought in the case of impoundment. In such cases water collection represents the prioritized supply method for human use and optimization objectives aim to maximize the 'collection capacity' of the reservoir. Water abstraction optimization, on the other hand, focuses on the withdrawal of water from the flowing river (e.g. diversion). An alternative for assessments targeting large basins that encompass several abstraction points is to define a 'supply objective' for each abstraction point in the considered system before defining the cumulative objective.

Hydropower generation objectives are typically considered for assessments targeting reservoir- (e.g. (Shiau and Wu, 2013; Wang et al., 2015; Fallah-Mehdipour, Bozorg-Haddad and Loáiciga, 2018) or basin-scales (e.g. (Paredes-Arquiola et al., 2013; Shiau and Chou, 2016; Hassanjabbar, Saghafian and Jamali, 2018). Hydropower production optimization objectives require the consideration of infrastructure operations and the infrastructure capacity in energy generation. When optimization objectives are focused on the economic aspect of hydropower generation from a reservoir, metrics such as net benefit or revenues are considered.

Definition of environmental objectives within the optimization procedure is connected to the environmental water management decisions (see Section 2.3) and usually considers the natural hydrograph or specific water volumes for ecological processes. Compliance of the regulated hydrograph with the natural discharge is based on the consideration of the natural flow regime as a pristine hydrological reference (Acreman, 2016). Despite increasing awareness of the need to advance the natural flow regime paradigm, whether or not species can adapt or are already adapted to flow alteration caused by man-made infrastructures (e.g. dams) remains difficult to assess and needs an 'expanded e-flow science foundation' (N. L. R. Poff, 2018). This leaves the natural flow regime alteration reduction as the easiest choice for many optimization assessments (Wang et al., 2015). Moreover, this approach does not explicitly prioritize specific species over others as in the ecological flow regime paradigm (e.g. (Suen & Eheart, 2006). Within the optimization procedure, gauge data at reference points can set the target conditions of the ideal flow regime (e.g. Torabi Haghighi and Kløve, 2015). Shiau and Chou, (2016) for example minimized the differences between the monthly flow hydrograph and the monthly discharge; similarly, Schlüter et al., (2005) minimized water flow changes across several intake points. However, the use of gauge data should be based on appropriate considerations regarding the location of the gauging station and the river section it is related to (e.g. drainage area or length of river segment), as this could affect the resulting scale of the assessment. As alternative to real flow data and to the flow-alteration-reduction approach, simple algorithms such as those in the Global Environmental Flow Calculator (GEFC) can rapidly calculate e-flow requirements for the main rivers worldwide (e.g. Hassanjabbar, Saghafian and Jamali, 2018). This information can be then used within the optimization problem for developing targeted releases or 'designer flows'. The designer flows approach is gaining momentum for preservation of river ecosystems (N. L. Poff & Olden, 2017) and has been embraced for example by Chen and Olden, (2017) to prioritize native over non-native species in regulated rivers.

Limiting conditions

Decisions about the range of limiting conditions to consider for the targeted assessment system can be distinguished based on their nature: (1) physical-environmental conditions, which refer to the environmental status of the system, e.g. conservation of mass; (2) supply-related, linked to the magnitude, timing, and type of demand; (3) infrastructure-related, that are influenced by the design or operational capacity of the flow modification structure (e.g. dam, hydropower plant); and (4) regulative, which are defined based on policies or normative requirements (see Table 4).

Physical-environmental limiting conditions reflect a certain environmental availability of water within the considered system and are usually described using a water balance equation or hydrological model. Our analysis showed that physical-environmental limitations are directly linked to the scale of the assessment. The location of the facility (i.e. dam, reservoir, hydropower plant, and weir) within the assessed area (e.g. basin, sub-basin, reach) influences the definition of the reference flow conditions and the number of inflow points. The targeted scale of the assessment is physically defined by the input location receiving the flow and an output location releasing the flow following the course of the river. Continuity equations are often used to capture and assure the balance between the inflows and the outflows (e.g. Xu et al., 2017; Hassanjabbar, Saghafian and Jamali, 2018). The definition of the continuity equation requires the consideration of the dynamics of inflows, hence of both location and timing. For example, the water quantity in a reservoir (dam) at a certain point in time (that depends on the considered timescale) is a function of the water contained in the reservoir (dam) at the previous time step (e.g. day, hour) and of the outflow and inflow water quantity at the current time step (e.g., Chen and Olden, 2017). The 'water budget' within a reservoir also needs to account for losses due to evaporation (e.g. (Porse, Sandoval-Solis and Lane, 2015). This is particularly relevant if the system is exposed to severe temperature fluctuations, dry conditions. Flows to and from groundwater systems and the hyporheic zone may also be relevant.

Limiting conditions can also reflect water or energy delivery requirements to meet sectoral needs (e.g. domestic, industrial, agricultural). Infrastructure operations optimization requires consideration of structural limitations on infrastructure capacity and releases. The number of infrastructure facilities and their management influences required scale and the corresponding constraints. Minimum (maximum) reservoir storage capacity or in- and outflow volumes are frequently implemented for water impoundment management, for example to avoid reservoir wall overtopping. This suits a daily or sub-daily scale optimization through the definition of the minimum and maximum allowable volume fluctuations (e.g. Chen and Olden, 2017) with respect to demand magnitude and risk of downstream bankfull flows or floods (e.g. Xu et al., 2017).

Water use agreements, treaty stipulations, and legal water rights can appear as limiting conditions depending on how the river network intersects with national or other jurisdictional borders (e.g. Porse, Sandoval-Solis and Lane, 2015; Wang et al., 2015). Quality standards (e.g. for irrigation, drinking water) are also common.

Table 4 **Framework 2/5.** Summary of the decisions and options, and related scale considerations for the ‘Assessment objectives‘ and ‘Limiting conditions’ steps during the ‘Problem perception phase’.

Assessment phase	**Modelling element**	**Decision**	**Description**	**Related options**	**Spatial scale relation**	**Temporal scale relation**	**Relationships between options**
Problem perception phase	*Management objectives*	Classification of water uses	Define water use objectives that are linked to the considered water flow alteration	• Energy generation • Water supply • Flood attenuation • Environmental health	Some objectives can be more strongly related to one scale (e.g. water supply or flood attenuation)	Need to consider the management horizon	This decision can be influenced by the decision on the extent of the assessment scale
		Contextualization of objectives	Consideration of the implication of objectives implementation within the case study area	• Participatory workshops with relevant stakeholders • User-defined • Regulations • Treaty stipulation	System boundaries do not change but need to consider the spatial scale in regulative terms	Could present different temporal needs in resource use (e.g. demand)	/
	Limiting conditions	Definition of the limiting conditions	Definition of the factors that can affect the nature of the considered objectives or the representability of the target system	• Natural phenomena • Structural limitations • Operational limits • Demand fluctuations • Hydrological continuity	Physical parameters (that can be spatially bounded e.g., hydrological continuity equation)	Consider time-dependence of some variables (especially demand, hydrology)	These conditions border the search space, allow the output of more realistic outcomes and reduce computational time

2.5.2 Problem formulation phase

Hydrological state and indicators

The decisions within the problem formulation phase specifically account for model, data, and computational limitations, contrasting with the ideal problem perception that stakeholders might prefer in absence of these limitations. In this phase, the definition of environmental water requirements establishes limits to the modification of water flows. We identified a series of crucial decisions related to the setting of environmental water requirements: the consideration of the preferred e-flow assessment approach, the inventory of the available sources of information, environmental water requirements establishment, and the location of the gauging stations and selection of the hydrological metric (see Table 5 for summary).

Environmental water requirements definition through empirical estimation of e-flow ranges is an option at finer scales (e.g. reach) and on short term planning (e.g. seasonal) when direct data (e.g., species, habitat-level data) is accessible. These ranges reflect hydrological or habitat needs (e.g. Mullick, Babel and Perret, 2013) of key species and can be defined through hydro-ecological models or regression techniques: for example, regression-based approaches to define fish-flow relationships for native and non-native species preferences (e.g. Chen and Olden, 2017) or by using the physical habitat simulation models (e.g. PHABSIM, (K. Bovee et al., 1998) to retrieve minimum e-flows requirements for phenological stages (e.g. (Shang, 2015). Mixed assessment approaches are more complex to implement as exploit multi-disciplinary instruments based on collaborative interactions between scientists, management analysts, and stakeholders (e.g. Porse, Sandoval-Solis and Lane, 2015).

Once the preferred approach is identified, multiple methods can be applied to obtain the necessary eco-hydrological information. Literature review and experts' involvement in the definition of water requirements for targeted species can be used for modelling and optimization of spatially complex systems (e.g. involving non-linear relationships and multiple predictors) as alternatives to massive data collection. Participatory workshops to set hydrological thresholds are underpinned by knowledge coming from different sources (e.g. Paredes-Arquiola et al., 2013), possibly measured at different scales in different locations, and hence require a more careful statement of the final scale of applicability of the assessment. Another option is the use of existing e-flow calculation software packages (see Section "*Management objectives*"). However, the modelling process can affect the spatial and temporal resolution of their output data and thus the final scale boundaries.

To define the reference hydrological conditions, and the monitoring of the targeted environmental assets, historical and actual data from gauging stations are used, potentially with hydrological model simulations. Flow data includes inflow data to reservoirs or dams when studies focus on optimizing release timing (e.g. Shiau and Wu, 2013). Whilst the number and location of gauging stations vary based on the study site type and the general purpose of the assessment, observations from gauging stations located downstream of the reservoir are useful for the assessment of water release alterations in single (e.g. (Yin, Yang and Petts, 2012) or multiple reservoirs in series (e.g. Dai et al., 2017). Moreover, analyses for multiple-reaches benefit from a sound gauging station network at the rivers and their tributaries as they enable the analysis of the variability of historical flows (e.g. Fleifle et al., 2014), while optimizing reservoir- or dam- series requires reporting or modelling of dam outflows (e.g. Yin, Yang and Petts, 2012; Shiau and Wu, 2013).

Our analysis showed that among the considered flow components, flow magnitude class parameters are widely used as hydrological indicators of ecosystem health within optimization studies as they reflect conditions that shape habitat availability and suitability for species (N. L. Poff & Zimmerman, 2010; Richter et al., 1996; Rolls et al., 2012; Rolls & Bond, 2017). Measures of the magnitude of monthly and annual flow conditions (e.g. median value of the mean monthly flow, minimum monthly flow) can describe the prevailing behaviour of the flow across the year or uncover major hydro-climatic cycles among different years (e.g. average yearly flow) but are unable to deliver sufficient information of local characteristics (e.g. reach-level behaviour). The disaggregation of monthly average flows into site-specific minimum monthly flows allows the consideration of the hydrological spatial variability at a sub-regional scale (e.g. Paredes-Arquiola et al., 2013). The water impoundment planning horizon (e.g. (Wang et al., 2015) or the characterization of a multi-reach system's behaviour (e.g. Shiau and Wu, 2013) can drive the choice of the selection of indicators defining the timespan and intensity in water flows (e.g. for low flow conditions). Similarly, baseflow indicators (often subdivided into wet, dry and extreme baseflow) are linked to reservoir outflow or diversion scheduling (e.g. Yin, Yang and Petts, 2012; Yin, Yang and Liu, 2014; Yin et al., 2015; Dai et al., 2017).

Water quality indicators (i.e. temperature, dissolved compounds, oxygen) are less frequently considered when addressing environmental flows problems (e.g. Fleifle et al., 2014; Xu et al., 2017). Nevertheless, these indicators are usually associated to the flow parameters to the extent of being affected by changes in the regime.

Table 5 **Framework 3/5.** Summary of the decisions and options, and related scale considerations for the 'Hydrological state and indicators' step during the 'Problem formulation phase'.

Assessment phase	**Modelling element**	**Decision**	**Description**	**Related options**	**Spatial scale relation**	**Temporal scale relation**	**Relationships between options**
Problem formulation phase	*Hydrological state and indicators*	Consideration of the preferred e-flow assessment approach	Selection of the suitable e-flow assessment approach defining environmental water requirements	• Habitat approach (habitat requirements of relevant species) • Phenological approach (life-history stages) • Holistic approach (mixed approach)	Need to consider the nature of targeted ecological endpoints (e.g. instream elements). Mixed approaches could be linked to multiple spatial scales and multiple resolutions	Needs to consider the targeted ecological outcome manifestation within the planning horizon	This decision could be linked to the decision on the considered number and nature of flow alteration structures
		Information inventory and method selection	Consideration of the available source of information	• Empirical estimation • Expert judgement • Web-tools • Literature • Participatory workshops	Data format could affect spatial scale. Need to consider the model resolution (if spatially explicit).	As for spatial scale, data resolution and empirical method could affect the temporal scale	This decision is directly linked with the previous decision on e-flow assessment approach. Could also affect scenario definition.
		Definition of reference hydrological conditions	Definition of the location of the monitoring or gauging stations as a source for	• Upstream of the reservoir • Downstream	System spatial boundaries could change when	Could be affected by historical data timeframe and temporal resolution	Represents mainly a data source, but can be linked with

			natural flow values and hydrograph data	of the reservoir • Multi-reach	including gauging station location		environmental asset location decision
		Selection of hydrological and non-hydrological indicators	Definition of the hydrological metrics (statistics) for the definition of threshold conditions (e.g. flow magnitude and frequency/timing)	• Flow magnitude • Frequency and timing • Extreme events • Water quality indicators	Infrastructure size could influence the extent of flow alteration	Indicator selection could be affected by the length of the considered timeframe (e.g. annual statistics can be used for multi-year planning)	This decision is linked to planning horizon needs, the nature and area of effect of flow alteration type as well as the scenario choice

Objective functions and decision variables

The previous problem perception phase creates the conditions for the translation of assessment objectives into objective functions. The general optimization problem is defined by the equation $f(x)$ that we seek to minimize or maximize, in which x is the decision variable in question (or vector of decision variables). In addition to deriving from the management objective, objective functions can differ considerably depending on data availability and the type of flow alteration type (e.g. run-of-river hydropower, storage-based power generation) (see Table 6). Selection of optimization objectives remains highly dependent on analyst choice and revolves around two main options: on one hand, a higher number of objectives (i.e. more than one) can favour a more comprehensive representation of the system while promoting an increased understanding of existing trade-offs; on the other hand, due to the structure of the applied technique, the optimization of multiple objectives is often hampered by limited computational capacity or difficult visualization of complex results (Lautenbach et al., 2013). Despite the existence of optimization tools able to model a higher number of objectives (see Reed et al., 2013), studies tend to keep the number of simultaneous objectives low (e.g. ≤ 4) as well as considering few decision variables (see Section "*Solution methods*"). In this case, the assignment of different weights to decision variables (e.g. Schlüter et al., 2005; Xevi and Khan, 2005) or the judicious use of constraints can reflect a range of stakeholders' preferences or policy decisions while at the same time reducing the computational effort. Further discussion on the number of objectives is presented in Section "*Constraint functions*" and "*Solution methods*".

The availability of exact and updated water consumption data for the targeted infrastructure can be challenging to obtain. Expressing water supply objectives as the minimization of shortage indices (e.g. long term total shortage ratio, mean annual deficit duration, maximum 1-day shortage ratio) allows the indirect consideration of demand by relying on daily reservoir releases (Shiau and Wu, 2013). Finer scale representation of water supply objectives, e.g. water demand-type at river network nodes (i.e. intake points) (e.g. Schlüter et al., 2005) allows a more refined optimization for complex reach systems. An alternative approach uses a composite function (e.g. an index) composed of different indicators for water use purposes, such as domestic, industrial, and agriculture supply (e.g. Suen and Eheart, 2006). Shares of abstracted water can sometimes be retrieved from regional and local databases, which may need to be downscaled or extrapolated to areas of interest.

The most straightforward way to optimize power production is through the maximization of water releases or available water volume for hydropower generation (e.g. Arslan, 2015; Xu et al., 2017) or inversely by minimizing the gap between generated hydropower and the installed capacity during operational periods (e.g. Fallah-Mehdipour, Bozorg-Haddad and Loáiciga, 2018). Yin et al., (2015) for instance, aimed at maximizing the mean annual revenue of hydropower generation concerning specific degrees of flow regime alteration. Likewise, economic objectives can be also set for studies targeting irrigation water demand (e.g. Xevi and Khan, 2005; Lewis and Randall, 2017).

In Section "*Hydrological state and indicators*" we discussed hydrological indicators used to define ecological needs. Here we present ways to employ those indicators within the optimization model. Environmental outcomes can be directly used as objective functions. In fact, e-flows objectives within the optimization problem are commonly expressed as specific share of incoming flow (usually expressed as volume) that reflect environmental requirements (e.g. Arslan, 2015; Xu et al., 2017). At the scale of river sections, habitat-level data availability allows optimizing specific river flow conditions for the benefit of target species (Chen and Olden, 2017). Depending on the targeted ecological endpoint, data collection and hence function definition can be more or less straightforward to perform. Reduction of the proportional deficit between a prescribed point-diversion and the river regime (e.g. Chen and Olden, 2017) suits assessments of finer-scale hydrological systems such as rivers and river sections. This also applies for assessments at reservoir-scale aiming at ensuring continuity between water inflows and outflows (e.g. Yin, Yang and Petts, 2012; Shiau and Wu, 2013; Steinschneider et al., 2014).

Lastly, the fitness of certain solutions to the objective function for the environmental water requirements can be conceptualized based on the assumptions of the analyst in relation to ecological response functions (Fu & Guillaume, 2014). For example, Suen and Eheart, (2006) considered the intermediate disturbance hypothesis assumption as basis for the definition of the fitness function for six eco-hydrological indicators to maintain the livelihood of aquatic ecosystems.

Constraint functions

The general objective function presented in Section "*Hydrological state and indicators*" is usually subject to some constraints. In the general case, $f(x)$ is subject to $g(x) < 0$, in which $g(x)$ represents the constraint function. Constraint functions can significantly influence the optimization outcomes, allowing the output of more realistic results with respect to the considered system scale and other factors (Strauch et al., 2019) in mathematical optimization approaches, whereas they commonly represent "decision maker preferences rather than physical laws" in simulation-based optimization (Clarkin et al., 2018). For the general definition of constraints and their effect on the objective function, see (Coello, Lamont and Veldhuizen, 2007).

Constraint definition can be a modelling-intensive phase if the system considers a high number of input points, diversion points, and facilities. If data used in the optimization problem is not yet spatially explicit (i.e. georeferenced), spatial boundaries are usually represented by considering intake and outtake points location.

While consumptive requirements can also be set as objectives (e.g. by defining a minimization function aiming at minimizing the gap between the target consumptive amount and the optimized amount), the translation of consumptive requirements into constraint functions requires knowledge of the nature of demand. Stable demands over time are easily expressed by estimating an amount of water that captures all the possible consumptive uses in the considered system. However, this choice will be more suitable for short time frames or long term averages, for example management plans for maintaining the native ecological communities in river sections (Chen & Olden, 2017). Alternatively, differentiating among demand types by setting a minimum water supply ratio can ensure compliance of reservoir operation with specific supply objectives, for example for irrigation purposes (e.g. Wang et al., 2015). On the other hand, a series of unpredictable factors (e.g. climate, social behaviour, and daily patterns) can also make the demand level uncertain. In this case, defining a reliable quantity of stored water for consumptive use or energy generation allows satisfying fluctuating needs over a longer period. In this case, a minimum storage constraint or supply reliability constraint may be used. The latter, in the case of municipal supply, can be also considered as objective depending on the problem structure (e.g. Yin, Yang and Petts, 2012).

Hydropower plant optimization objectives are frequently constrained by capacity thresholds limiting the range of decision variables such as the control gate operations, turbine release, ramping, power tunnel, and grid capacities defining power output limitations (e.g. Steinschneider et al., 2014; Dai et al., 2017).

Optimization process-related constraints have the purpose of facilitating the search phase by setting specific conditions that will influence the fitness value based on the degree of violation (e.g. Dai et al., 2017). Penalty functions are an example of constraint handling techniques, where a constraint function is transformed into a penalty that is directly added to the objective function (Coello et al., 2007; Ruhul et al., 2012). For example, penalties can be set based on the frequency of falling outside of the target range for each e-flow parameter (e.g. Wang et al., 2015). However, the values of the penalties should not be set to very large values to avoid interfering with the identification of the ideal fitness values (Dai et al., 2017).

Lastly, constraints can also reflect additional objectives thus reducing the number of objectives (e.g. to a single objective) (e.g. Torabi Haghighi and Kløve, 2015; Wang et al., 2015) but this does not necessarily mean that problem size would be reduced. Conversely, constraints can also be turned into objectives, thus increasing their number and eventually leading to many-objective problems. However, Kasprzyk et al., (2016) in their study of many-objective problems for water management showed that a higher number of objectives can be paradoxically easier to solve.

Table 6 **Framework 4/5.** Summary of the decisions and options, and related scale considerations for the 'Objective functions and decision variables ' step during the 'Problem formulation phase'.

Assessment phase	**Modelling element**	**Decision**	**Description**	**Related options**	**Spatial scale relation**	**Temporal scale relation**	**Relationships between options**
Problem formulation phase	*Objective functions and decision variables*	Consideration of the number of objectives	Definition of objectives number based on the computational effort	• Single-objective • Multi-objective	Objectives for different water uses are often on different spatial scales or extents	Objectives calculated on longer timeframes often need to be complemented with objectives that capture shorter-term variability	Relates mainly to computational resources but can be influenced by the solution method decision.
		Consideration of the nature of objectives	Definition of the type of objective function that can solve assessment needs	• Supply reliability indices • Shortage indices • Composite functions (weights assignment) • Gap reduction	Requires knowledge of the environmental asset	Requires knowledge on management horizon and information on demand nature	Relates to the solution method and is mainly methodological.
	Constraint functions	Consideration of the nature of constraints	Selection of the type of constraints that would allow the best representation of the targeted system	• Upper and lower limits on decision variables (e.g. storage capacity) • Search-related constraints	Requires knowledge of infrastructure operations, location, and type of flow alteration	Need the consideration of the management scenario and planning horizon	Relates to the decision on the type and number of objectives

Solution methods

How a water allocation optimization problem is addressed across the different scales depends on its overall complexity. There is no direct relationship between scale and solution method as too many factors influence the selection of one technique over another. Moreover, problems can be approached with different degrees of complexity even if the considered assessment scale is fine (e.g. a single facility). However, since water allocation optimization is based on the mathematical conceptualization of the problem (e.g. linear, nonlinear, discrete, and continuous), knowledge about differences in solution approaches can contribute to the understanding of possible solving strategies for the considered scale (system) based on components (e.g. indicator types for objectives, nature for constraints). To illustrate the decision about the solution method, we distinguish between deterministic (or mathematical programming) and meta-heuristic optimisation.

Our analysis showed that oftentimes water allocation problems are formulated as multidimensional, convex objective functions constrained by a series of rules. Since constraints influence the geometry of the feasible solution space, the solution can be found through the process of eliminating problem variables (Cavazzuti, 2013). For example, linear programming-based algorithms have been used for solving broad-scale optimization problems of system types involving dams and large reservoirs, showing a convexity both in the objective function and in the constraint functions (Xevi and Khan, 2005; Steinschneider et al., 2014; Porse, Sandoval-Solis and Lane, 2015; Chen and Olden, 2017). Problems envisaging variables with a high degree of nonlinearity (e.g. evapotranspiration, soil infiltration) can be solved by elimination-based nonlinear programming algorithms (e.g. Schlüter et al., 2005; Arslan, 2015). In the case of broad-scale optimization problems considering quadratic equations envisaging the relationship between streamflow and net economic benefit, sequential quadratic programming can iteratively search for the optimal solution (e.g. Mullick, Babel and Perret, 2013). When continuous function variables show discrete or integer values, mixed-integer linear programming is preferred instead. Wang et al., (2015) used this technique to optimize large scale reservoir operations carrying a binary value in the reservoir outflow parameter.

Metaheuristic optimization algorithms can handle problems characterized by a high number of objectives (Coello et al., 2007; Maier et al., 2019). This could be the case of multi-purpose or multi-reach optimization problems. As a sub-group of metaheuristics, evolutionary algorithms provide good chances of approximating a globally optimal solution quite rapidly (Cavazzuti, 2013) by generating initial random sets of variables and then by exploiting operators such as selection, mutation and cross-over to produce better solutions at each generation. For example, Fleifle et al., (2014) solved the minimization problem for the wastewater treatment costs and maximized water quality in a river section. Evolutionary techniques such as the non-sorted genetic algorithm (NSGA) are commonly applied for handling both basin and multi-reach scale optimization problems (e.g. Suen and Eheart, 2006; Dai et al., 2017; Martin et al., 2017; Xu et al., 2017).

Optimization scenarios

The definition of optimization scenarios is included in the problem formulation phase as it relates closely to the practicalities of providing useful information in the face of data, model, and computational limitations. In principle, a given problem formulation would ideally have a general solution, but in practice, it needs to be embedded in a specific context, and multiple variants of problem formulations may be possible. The context represents both environmental, operational and management conditions. Scenarios hence provide the opportunity to assess alternatives based on system behaviour under possible circumstances (e.g. on the effects of different release-schemes on hydrological variability or seasonal conditions on planned abstractions). This could contribute to reduce uncertainty about a specific management decision or to explore potential management decisions, under a range of operational, ecological and hydrological conditions. For example, Lewis and Randall, (2017) considered dry, normal and wet hydrological conditions; Porse, Sandoval-Solis and Lane, (2015) considered different e-flow allocation targets to assess the trade-off with water supply; Wang et al., (2015) formulated scenarios representing combinations of objectives and constraints. While the reliability of optimization outcomes can be also linked with robustness and accuracy of output data, it also depends on prior knowledge about the considered system which is itself based on the overall system understanding Sanchis, Martínez and Blasco, (2008). This means that some degree of conceptual bias arises from our lack of understanding of relationships between components. The size and type of investigated system influences the scenarios that have to be evaluated, because different needs, and thus ways to think objectives, can exist within that system domain. For example, if the system is large (e.g. river basin, sub-basin) multiple needs often need to be addressed due to the presence of different social groups and economic activities, policy requirements (e.g. Porse, Sandoval-Solis and Lane, 2015) or just the presence of multiple abstraction points (e.g. Paredes-Arquiola et al., 2013). Scenarios can be expressed differently for single facility systems. At the reservoir scale, alternatives could be represented by the compromises between the amount of released and impounded water flow concerning natural flow variability or e-flow requirements. Scenarios depicting trade-offs between a series of off-stream (e.g. irrigation) and instream benefits (e.g. fishery) can be assessed with and without e-flows as a constraint (Mullick, Babel and Perret, 2013) to promote the incorporation of e-flows within a water management plan.

Table 7 **Framework 5/5.** Summary of the decisions and options, and related scale considerations for the 'Solution methods' and 'Optimization scenarios' steps during the 'Problem formulation phase'.

Assessment phase	**Modelling element**	**Decision**	**Description**	**Related options**	**Spatial scale relation**	**Temporal scale relation**	**Relationships between options**
Problem formulation phase	*Solution methods*	Solution search approach	Selection of the solution approach based on the nature of the considered decision variables and related functions	• Mathematical-based • Stochastic	Complex problem formulations covering multiple spatial scales may not be computationally feasible, requiring simplification	Longer management horizons and finer-scale operations may require longer model run times	This decision is highly linked with the decision on the number and nature of objective functions (and computational resources availability)
	Optimization scenario	Definition of the uncertainty sources/external conditions	Consideration of the major source of uncertainty in optimization outcomes	• Climatic conditions • Hydrological • Operational horizon • Legislative	Need to consider the extent of the river network and the type of facility	Connected to management horizon, if set at an annual scale could highlight inter-annual patterns	This step is influenced by the optimization model purpose (i.e. updating an existent plan or propose a new one)

2.6 Discussion

2.6.1 Need for clarity of problem definition

Complex environmental water allocation problems can be optimised for a range of regulated system types (e.g. river basins, reservoirs, reaches, hydropower plants) considering conflicting water management objectives (i.e. aquatic ecosystems livelihood and human supply). Overall, the definition of system scales and conceptualization within optimization procedures reflects a well-known problem-oriented perspective on the river system (van den Belt and Blake, 2015; Opperman et al., 2018), intended to meet the functions required for management purposes, and therefore requiring transparent documentation of the management problem.

The availability of optimization models that can be applied simultaneously to multiple scales is still limited. Studies would rather formulate the problem for one target area at a time. Hence, the applicability of an optimization framework is generally only suitable to the specific case study or systems with similar relevant features (e.g. the presence of a hydropower generator) (e.g. Yin, Yang and Liu, 2014). In general, this results in a limited reproducibility of a scale-specific optimization assessment for environmental water management - which could hinder the interpretation of results by decision-makers. This review and the resulting framework therefore highlight the need both for clear problem definition and efforts to develop the tools necessary to address multi-scale problems as defined.

2.6.2 Need for strategies to implement desired assessment scales

The size (i.e. temporal and spatial scale) of the assessment is intrinsically connected with the range of information needed for the development of the optimization procedure. Optimization of large systems (e.g. basins, transboundary rivers) and long planning horizons (e.g. multi-year planning) requires more complex decision making about suitable options as information could be nested and hence more challenging to obtain. Problems involving larger systems may be divided into smaller components by subdividing the system into shorter time-frames or sub-areas. This operation when possible may reduce both computational and modelling effort. Conversely, smaller systems (e.g. river sections, reaches) modelling require less difficult option selection but could still be as challenging as more demanding solution approaches (e.g. modelling ability) might be needed. However, mismatches between the scales of involved factors (e.g. management scale, hydrological scale) during modelling are frequent as scales are defined based on different needs (i.e. administrative, modelling). Overall, this can compound the difficulty of defining absolute assessment scales because of the many factors involved (see Figure 3). It may be hence more appropriate to speak of the targeted system 'boundaries' rather than scales more generally (van den Belt & Blake, 2015). Moreover, improved knowledge of the system connections (i.e. river system) at the basin scale would also be helpful to better understand the effects of local-scale flow regulation structures. This is especially meaningful if the final aim is to balance water needs as part of a wider system (i.e. basin) (Shiau & Wu 2016).

2.6.3 Need to make explicit trade-offs in model development

Decisions and option selection during optimization problem definition are usually nonlinear with respect to targeted assessment scales, as some trade-offs in data availability and modelling requirements need to be accounted for. This is due to the fact that the relationship between scale and available options is not one-to-one. The development of optimization procedures to solve water management problems requires the simultaneous consideration of multiple factors to representatively recreate the real context or system: the targeted scale from the management perspective (e.g. basin) on which a certain environmental goal applies (e.g. good ecological status); the number of involved infrastructures and their location; the location of gauging and monitoring stations within the management area; and the possibility for the considered system to cross geopolitical borders. Hence, this revolves around the need to gather sufficient information to be able to represent the targeted system; or, to adapt the assessment scale to the data available (i.e. reducing the problem size into smaller problems or 'nested' systems). Failing to clearly describe the optimization problem context (e.g. physical system, management horizon, and objectives) reduces the understanding of how to represent trade-offs and results in a less transparent treatment of scale, and therefore the ability to model across scales.

2.6.4 Need for increased modelling capacity

Solving water management optimization problems at different scales presents some challenges in relation to the nature of the decision variables, the increasing number of objectives and the nature of the functions (Reed et al., 2013). Whilst the fact that initial accessible information (i.e. in the problem perception phase) linking flows, infrastructure operations and environmental outcomes "is not readily available in a format suited to optimization" (A. Horne et al., 2016), a major impediment is represented by limited modelling capacity. When dealing with complex real-world problems this could drive to over-simplification and thus reduced reliability in optimization outcomes. On the one hand, a solution to over-simplification could be the use of more sophisticated algorithms able to deal with a higher number of objectives, as many-objective optimization algorithms are able to deal with up to 15 objectives (Chand & Wagner, 2015), though this would inevitably lead to increase in needed computational effort. On the other hand, consideration of the more appropriate approach (i.e. robust or evolutionary) based on the temporal horizon of the problem (e.g. infrastructure scheduling, management planning) could reduce the overall uncertainty as it would account for the level of decision making incorporation (Grossmann et al., 2016). Lastly, improving the flexibility in optimization problem structure (e.g. by finding a benchmark model structure) to be applicable for different scales (e.g. Shiau and Wu, 2013) could help discover nested trade-offs within the same study system or similar systems thus by fostering comparison.

2.7 Outlook and recommendations: Using optimization procedures in water management

The need for stating clearer reference boundaries in study descriptions has already been identified by Gleeson and Paszkowski, (2014). We consider this even more significant for optimization problems, particularly concerning decision-making transparency throughout model development around the final assessment scales. Clear definition of targeted and modelled spatial and temporal scales within optimization procedures for environmental water allocation could support the identification of potential minimum thresholds (i.e. scale) at which e-flow management should be implemented. However, this process requires an increased understanding of how modelling limitations relate to option selection. We believe that unravelling the relationship between existing options between the problem formulation phase and the modelling phase provides a useful pathway for improving the take-up of results at the right management level and increasing our ability to model across scales. The first step in this process would be clear communication of the optimization problem statement throughout the two phases (see Section 2.5). This may also include discussion of how the problem design can be altered to increase understandability, which can also improve the understanding of system trade-offs (Seppelt, Lautenbach and Volk, 2013).

2.7.1 Towards increased transparency: recommendations for optimization problem development

The framework provided in Section 2.5 mapped the crucial decisions and options related to each phase of model development (the problem perception phase and the problem formulation phase) and the implications for the temporal and spatial scales of each stage. In this section, by building on the aforementioned framework, we propose recommendations for model development under the form of essential questions that need to be addressed. This questionnaire, presented in Table 8, assists system conceptualization and serves to check information availability. By doing so, it supports clarity in problem translation from the problem formulation to the modelling phase.

We believe that making the role of information availability explicit throughout model development will support system understanding and further foster transparency around the trade-off process in model development and system scale representation when defining an optimization model for water management problems.

Table 8 **Series of key questions that need to be addressed during optimization model development for water management.** The table presents questions for each optimization phase.

Problem perception phase

Physical system

- *How many flow-altering infrastructures are involved? What is the nature of the flow alteration? What types of operations are performed?*
- *What is the timeframe of the operational scheme?*
- *How frequently does the infrastructure management plan need to be updated?*
- *What is the scale of effect of the flow altering infrastructure operations?*
- *What are the targeted environmental assets? What are the ecological endpoints for the targeted environmental asset? What is the location of the environmental asset and ecological endpoint?*
- *At what scale are the ecological outcomes manifested?*

Management objectives & Limiting conditions

- *What are the management objectives for the considered management horizon?*
- *How are management objectives defined?*
- *What is the temporal scale of the considered objectives?*
- *What are the limiting conditions that characterize my objectives?*
- *What are the bounding conditions that characterize the problem setting (e.g. structural, hydrological)?*
- *What is the temporal dependence of the limiting conditions?*

Problem formulation phase

Hydrological state and indicators

- *What is the source of hydrological information?*
- *What is the temporal resolution of the hydrological information?*

- *What is the location of the gauging stations?*
- *What assessment approach is used to represent the requirements?*
- *What instrument/tool/source of information is used to define the environmental water requirements for the targeted environmental asset? What is its spatial/temporal resolution?*

Objective functions, decision variables, and constraint functions

- *What hydrological metrics are representative of the selected ecological endpoints?*
- *Do the hydrological metrics match the planning horizon?*
- *What and how many decision variables are needed to represent the problem objectives?*
- *How many and what functions are needed to represent the problem objectives and constraints?*
- *What is the nature of the considered decision variables (discrete, continuous)?*

Solution methods

- *What computational/modelling resources are available to handle the selected functions?*
- *What approaches are implemented to reduce computational/modelling effort?*

Optimization scenario

- *How is uncertainty in optimization outcomes addressed?*
- *What is the uncertainty in climatic conditions?*
- *What is the uncertainty in hydrological information used?*
- *What is the uncertainty in the operational horizon?*

2.10 Conclusions

This review paper analysed the implications of decisions and related options throughout the optimization model development stages for the final temporal and spatial scale of the assessment. We first explored the main decisions that have to be made by distinguishing two distinct phases in optimization problem development: problem perception and problem formulation. We found that most decisions have strong links with the spatial and temporal scales of the assessment that need to be accounted for. Successively, we mapped options related to each decision (i.e. related to the physical system, assessment objectives, the hydrological state and indicators, objective and constraint functions, solution methods and, optimization scenario) and provided scale-specific considerations for option selection.

Overall, given that water management problems involve a large number of factors to consider (e.g. operations schemes, supply competition, changing environmental conditions), the decision-making supported by optimization techniques is influenced by a series of challenges related to data availability and modelling capability. This consequently affects decision making about options, which resolves in tailoring the optimization model to the available data and modelling ability, retrieving additional data required or subdividing the problem. Further research focused on clarifying the underlying influences between options concerning scale would provide an enhanced insight into the relationship between options and improve the process of option selection. Besides, it would enable the integration of instruments that can improve reliability and comparability in optimization outcomes. Moreover, while exploring how trade-offs across scales are incorporated into the optimization process is more challenging for the application of optimization algorithms; it is also potentially most useful to an environmental water manager. As a foundation for these goals, we provided recommendations for model development by focusing on key questions related to each decision, with the intent of fostering transparency around decision making and options selection during both problem development phases.

3. Applying optimization to support adaptive water management of rivers


water

MDPI

Article

Applying Optimization to Support Adaptive Water Management of Rivers

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References to Supplementary Materials can be found in *Appendix B* attached to this thesis.

3.1 Summary (abstract)

Adaptive water management is a promising management paradigm for rivers that addresses the uncertainty of decision consequences. However, its implementation into current practice is still a challenge. An optimization assessment can be framed within the adaptive management cycle allowing the definition of environmental flows (e-flows) in a suitable format for decision making. In this chapter, we demonstrate its suitability to mediate the incorporation of e-flows into diversion management planning, fostering the realization of an adaptive management approach. We used the case study of the Pas River, Northern Spain, as the setting for the optimization of surface water diversion. We considered e-flow requirements for three key river biological groups to reflect conditions that promote ecological conservation. By drawing from hydrological scenarios (i.e., dry, normal, and wet), our assessment showed that the overall target water demand can be met, whereas the daily volume of water available for diversion was not constant throughout the year. These results suggest that current the decision making needs to consider the seasonal time frame as the reference temporal scale for objectives adjustment and monitoring. The approach can be transferred to other study areas and can inform decision makers that aim to engage with all the stages of the adaptive water management cycle.

3.2 Introduction

The concept of integrated water resource management (IWRM) embodies the willingness to account for the economic, social, and ecological implications of water management (Meran et al., 2021). River regulation such as damming, barrages and river training can affect both the sediment balance, inducing morphological changes, and the hydrological regime (Bizzi et al., 2015; Ely et al., 2020). As a consequence, many of the current water management decisions for regulated rivers worldwide aim for the sustainable use of water resources to protect the natural ecosystems (Tharme, 2003). However, the rapid decline in freshwater biodiversity urges for prompt practical actions such as environmental flow implementation (Lemm et al., 2021; Tickner et al., 2020). The concept of environmental water regime or environmental flow (e-flow) has been first announced during “The Brisbane Declaration” (2007) (*The Brisbane Declaration*, 2007) and ever since it defines “*the quantity, timing, and quality of water flows required to sustain freshwater and estuarine ecosystems and the human livelihoods and well-being that depend on these ecosystems”* (Acreman, 2016; Acreman et al., 2014; Arthington, Bhaduri, et al., 2018; Arthington, Kennen, et al., 2018).

In regulated rivers, sustainable use is typically achieved by management decisions controlling certain variables such as consumption capping or water allocation through downstream release for specific target ecological processes and/or components (A. C. Horne, O’Donnell, & Tharme, 2017). Whatever the management decision in question, the incorporation of e-flows into practice is fundamental to facilitate “the establishment of a water regime needed to manage rivers” (N. L. Poff et al., 2017) that acknowledges the importance of ecosystem needs (Tharme, 2003). Moreover, e-flows incorporation within management practices can also be associated with conservation and restoration objectives for the targeted scales such as “passive” restoration approaches addressing the reduction of hydrological alteration stresses on biodiversity (Arthington, 2015; Atkinson & Bonser, 2020; King et al., 2015; Opperman et al., 2019).

The complexity of interactions characterizing our socio-ecosystems (sensu Iwanaga et al., 2021) leads to difficult predictability of effects of certain factors (e.g. climate, water demand) that increase the uncertainty of results from specific water management actions (Pahl-Wostl et al., 2007). This lack of security exacerbates the ongoing challenges on decision making in the water management process such as organizing efficient water governance systems (Pahl-Wostl et al., 2012) and leads to reduced capacity to resolve unexpected eventualities and future scenarios. The concept of “adaptive management”, as a fairly new paradigm for managing water resources in an integrated way, emerged in the last decades in response to the need for improving water management strategies (Medema et al., 2008; Webb, Watts, et al., 2017). This paradigm, which builds on the ‘learning-by-doing’ approach, considers the improvement of management practices by learning from the outcomes of previously implemented management strategies (Pahl-Wostl et al., 2007; Webb, Watts, et al., 2017). Theoretically, this process consists of a constant loop of learning and adaptation between each adaptive water management cycle (AWMC) to achieve long-term management goals (e.g. restoration of hydrological conditions for endemic species). However, smaller adjustments based on shorter-term ongoing outcomes could be made between each phase of the cycle (i.e. planning, doing, monitoring, and learning; see Docker & Johnson, 2017; Doolan et al., 2017; Webb, Watts, et al., 2017. Practically, exact strategies to achieve adaptability within the AWMC are still lacking (Edalat & Abdi, 2018) – it calls for stronger links between the management actions and subsequent monitoring strategies (Docker & Johnson, 2017c; King et al., 2015; Westgate et al., 2013) to support the evidence of ecological improvement or degradation (Westgate et al., 2013).

The adaptive management approach suits the challenge of incorporating e-flows into management (due to the uncertain nature of environmental outcomes after management decisions; (A. C. Horne, O'Donnell, Acreman, et al., 2017; Williams & Brown, 2016). The practical incorporation of e-flows into water management planning will require prompt adaptation of decisions and actions based on changing environmental conditions (e.g. hydrological, ecological, and climatic). The prediction of results from management actions under different scenarios (e.g. incorporating hydrological variability, climate change, and demand fluctuation) before their implementation represents a very powerful tool to anticipate consequences and reinforce the decision-making process to improve adaptability, sustainability and, ecosystem conservation. Overall, such a strategy will improve our ability to reveal management effects in complex systems as managed rivers (Medema et al., 2008).

E-flows incorporation into water management is often linked to the problem of balancing human and ecosystem water needs and maintaining ecosystem services provision when sustainable abstraction practices are sought. Different methods have been applied to support water management and water allocation in complex systems. Examples include economic approaches (Haavisto et al., 2019; D. Wang et al., 2019); geographic information systems (Gebru & Tesfahunegn, 2020; Neissi et al., 2020); socio-hydrological and environmental assessments (Baker et al., 2015; E. G. R. Davies & Simonovic, 2011; Mostert, 2018); as well as a range of decision-support tools (Maia & Schumann, 2007; Ruiz-Ortiz et al., 2019). Usually, water management deals with a range of conflicting anthropogenic water use objectives and consequently, there are important trade-offs between water uses and demands (Mendoza & Martins, 2006). The need for new instruments and frameworks that help decision-makers is still evident (A. C. Horne, O'Donnell, Acreman, et al., 2017) and will increasingly put pressure on water managers dealing with future climate change effects (Burnham et al., 2016; Hart et al., 2017). Optimization is a decision support approach that has been applied for such water management problems at different scales, envisaging convoluted decision-making (among which are trade-offs in river ecosystem services and river sediment budget maintenance; (Bernardi et al., 2013; Bizzi et al., 2015; Laurita et al., 2021; Derepasko, Guillaume, et al., 2021; Dhaubanjar et al., 2017; A. Horne et al., 2017). It enables the identification and evaluation of trade-offs and synergies among some management objectives (e.g. control of consumption, risk prevention, delivery of water for targeted species, hydropeaking control) before the implementation takes place. The technical structure and features of the optimization approach (e.g. mathematical expression, multiple solutions) address many of the challenges (e.g. scenario analysis, real-world conditions representation) resulting from the need of incorporating e-flows into management planning (Derepasko, Guillaume, et al., 2021). Due to the absence of exact rules for the definition of e-flow requirements for rivers but rather distinct approaches (Lamouroux et al., 2017; N. L. Poff et al., 2017; Webb, Arthington, et al., 2017), a series of strategies are possible to operationalize their incorporation within the optimization assessment (e.g. based on the consideration of natural-flow conditions or exploiting flow-biota correlations). Careful definition of e-flow requirements is hence needed to support the monitoring phase and enabling the adaptive process (King et al., 2015; Webb, Watts, et al., 2017).

In this paper, we propose an optimization assessment on the example of a targeted river basin in Northern Spain, which is providing water for an urban area of over 200’000 people. The specific objectives of the modeling exercise were (1) to demonstrate the suitability of a new methodology based on an optimization approach to mediate the incorporation of e-flows into the diversion management planning, (2) to discuss the challenges and limitations of the optimization model by drawing from the considered water management problem, and (3) to assess the potential of the optimization approach to foster adaptive management of water resources. We first present the conceptual framework underpinning the definition of the optimization assessment for water abstraction and the stages involved in the definition of the optimization problem for the selected case study (*Section 3.3*). The section also contains the description of the case study and the optimization problem incorporating environmental flows, as well as an illustration of the hydrological scenarios and the optimization modeling algorithm. Simulation results are presented in *Section 3.4*. Lastly, we discuss both the modeling assumptions and results, highlighting both the advantages and the disadvantages of the optimization assessment, and the implications for the diversion planning and river management providing suggestions for the best adoption of an adaptive process (*Section 3.5*).

3.3. Materials and Methods

3.3.1 The optimization framework

The optimization assessment framework presented in this study represents the “structured set of steps and considerations used for the formulation [of the optimization problem]” (Derepasko, Guillaume, et al.,

2021) underpinning the optimization modeling exercise carried out at the example of the Pas River, Northern Spain (*Paragraph 3.3.2*).

The stages of the optimization assessment framework that led to the definition of the optimization problem for the case study and their relation to the AWMC phases (see Figure 5) are shown in Figure 6. As a first step, management objectives and water allocation decisions for the Pas River basin have been assessed to understand the problem context and identify priorities and water diversion practices (*Paragraph 3.3.2*). This stage required the contextualization of the optimization problem to identify the best output information to be produced. In other words, a tailored result format has been selected to enable the usage of information by the targeted user type (i.e. water managers and decision-makers). Successively, based on the information identified during the contextualization phase, reference e-flow conditions have been defined considering different biological groups present in the ecosystem (*Paragraph 3.3.3*). For these biological groups, hydrological conditions (expressed as thresholds) have been considered to preserve flow components from alteration caused by diversion. The "learning" process within the AWMC is based on the exploration of ecological effects from the management interventions (Webb, Watts, et al., 2017). As described in *Paragraph 3.3.3*, given the exploratory nature of the assessment, the hydrological thresholds on the flow components (for each biological group) considered in this study were

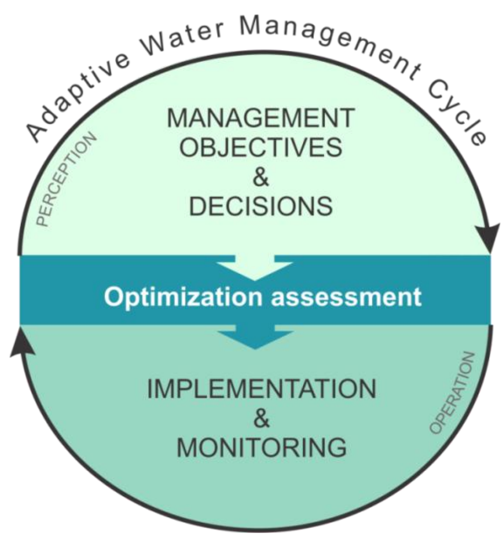


Figure 5 **Position of the optimization assessment within the Adaptive Water Management Cycle.** The phases of an AWMC can be divided into two main stages belonging to opposite edges of the action spectrum, the perception-understanding and operational: the first stage involves the definition of the management objectives and management decisions; the second stage focuses on the implementation and monitoring of the management actions to provide insight into the next cycle, respectively.

largely based on expert judgment. Lastly, information collected from the two previous stages was processed during the modeling stage which considered the design of the optimization problem (e.g. solution approach) and its functions (i.e. objectives) both for the human water demand and for the considered biological groups (*Paragraph 3.3.4*). Alongside the model development, hydrological scenarios reflecting daily mean discharge at the targeted location have been developed and used as the reference (input) hydrological conditions for the optimization model runs (*Paragraph 3.3.5 and 3.3.6, respectively*).

3.3.2 Case study area: The Pas River basin

We used the Pas river basin in Northern Spain as the case study area for the optimization assessment development and application (Figure 7). The Pas River represents an ideal catchment to show the potential of optimization approaches to support adaptive water management planning. It is subjected to relatively strong human pressure while it still provides a good representation of its potential natural condition. In this regard, most of its river water bodies show a good ecological status (sensu European Water Framework Directive; EC, 2000) and provide habitats for iconic species for conservation, such as the

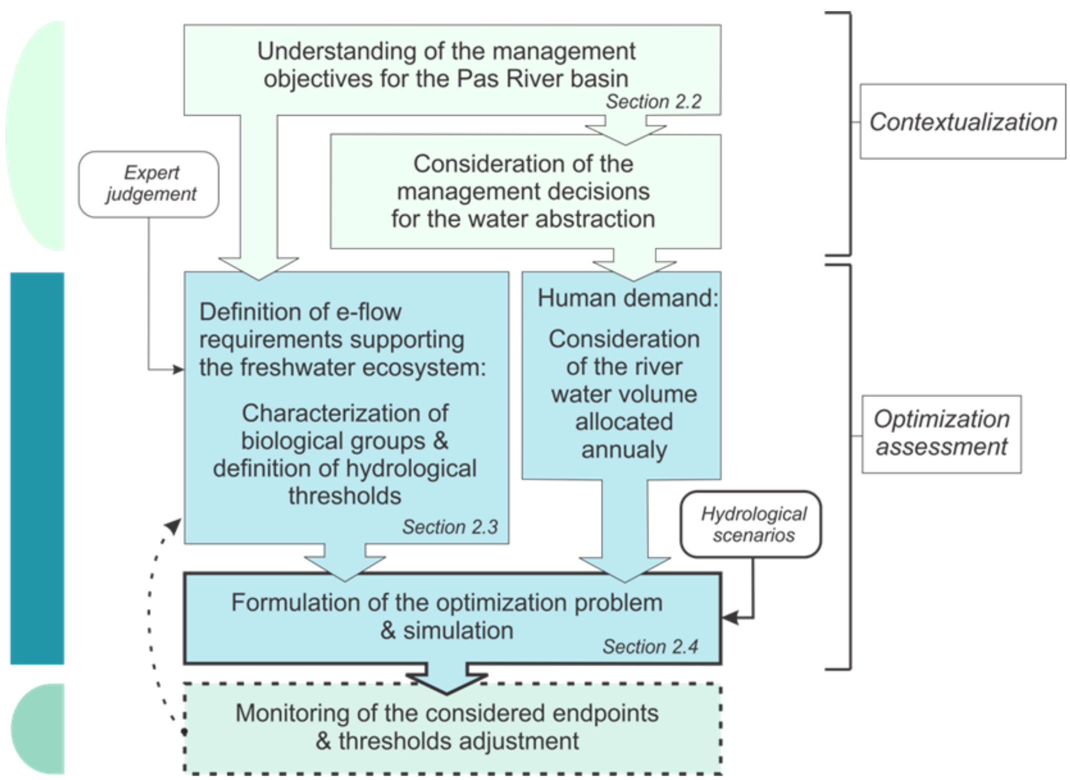


Figure 6 **Structure of the applied optimization assessment.** The case study description phase considers information that arises from the current management decisions and it was used for the optimization assessment development. The bold-outlined box corresponds with the monitoring phase that was not assessed in this study but serves to highlight the link with the Adaptive Water Management Cycle (left-hand side).

Atlantic salmon. The Pas river system drains into the Cantabrian Sea (North-East Atlantic). Calcareous rock and sandstone formations dominate the basin which covers an area of 649 km^2. The river network is defined by the three main rivers Pas, Pisueña, and Magdalena. The mean annual precipitation amounts to 1300 mm, and the mean annual daily flow (close to the river mouth) is 14 m^3/s. Maximum flows are observed in April, and minimum discharges occur in September (Álvarez-Cabria et al., 2010), close to the mouth. Water regulation in the basin is mainly implemented through surface water uptake by cross-channel weirs and pump injection into the water supply grid. A primary management objective is domestic water supply: water is mainly abstracted to satisfy the demand of the municipalities with annual volumetric allocation for the distinct municipalities. While there is no large infrastructure (e.g. dams) able to modify high flow and flood patterns, water diversion operations and water use can still influence the hydrological attributes related to low flows (e.g. magnitude of low flows, duration of droughts). Extended shoals and changes in the river flow as a consequence of traditional diversion practices represent a threat to ecosystems and freshwater biota. The ecological conditions of the aquatic ecosystem in the basin are monitored and defined by the Cantabrian Hydrological Confederation (CHC) which is also responsible for the drafting and development of the Basin Management Plans. In this study, we considered as a setting for the optimization of water abstraction for municipal use two distinct diversion points (DP1 and DP2) - as consumptive demand for the points we considered 0,26 Hm^3/y and 0,66 Hm^3/y, respectively. Both points are not impacted by prior upstream flow diversion along the river network located on two distinct river segments (*sensu* Derepasko et al., 2021).

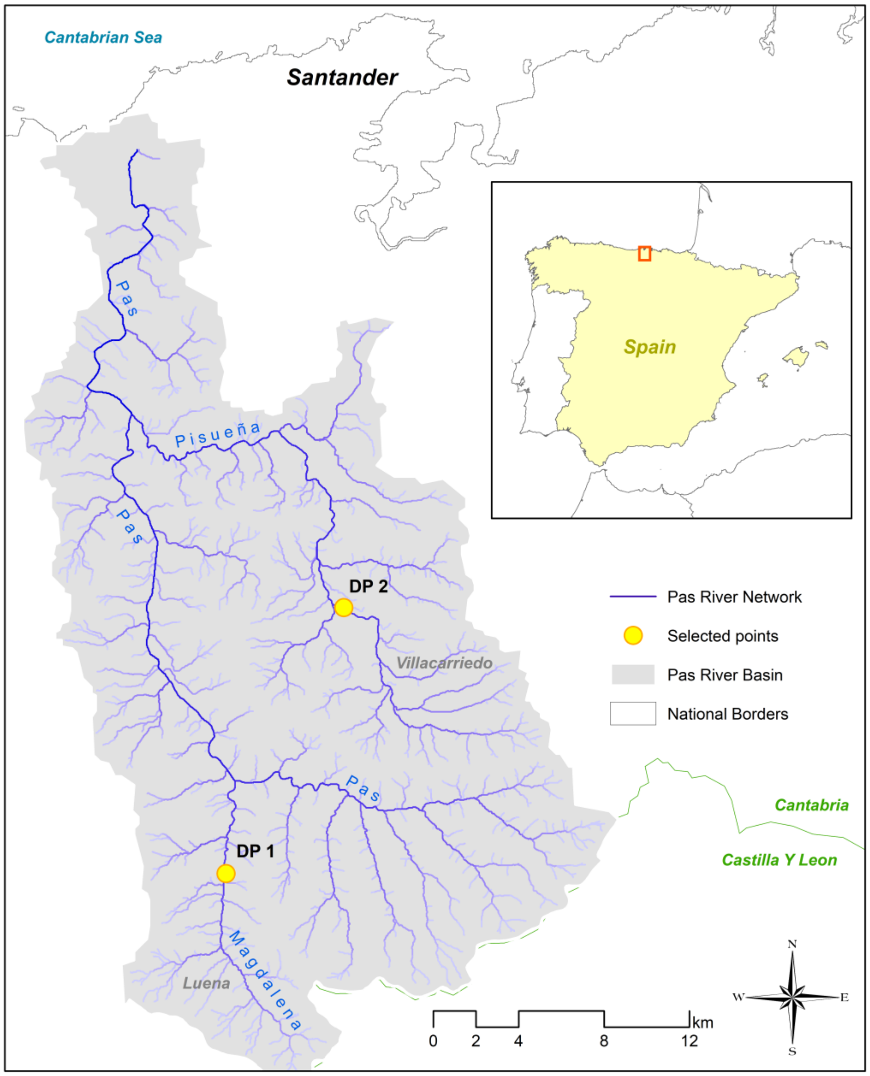


Figure 7 **Location of the Pas River Basin and the river sections in proximity to the selected diversion points (indicated as 'DP').** For illustration purposes, we added shading to the river network, linked to average river discharge.

3.3.3 Definition of the e-flow requirements for the Pas River: biological groups and hydrological thresholds

The optimization of water diversion based on environmental needs requires the definition of reference hydrological conditions to ensure the conservation of key flow attributes (e.g. base flows, pulses, etc.) that support the ecosystem. Knowledge of the exact hydrological conditions for species and their cross-scale variation remains a core research gap in the field of freshwater biology (Rolls et al., 2018). Despite this gap, water management optimization assessment relies on flow-ecology relationship assumptions or eco-hydrological indicators (e.g. Chen & Olden, 2017; Shiau & Chou, 2016; Torabi Haghighi & Kløve, 2015; X. A. Yin et al., 2012) for the identification of optimal management strategies that facilitate the implementation of an adaptive management approach at appropriate scales (Dollar et al., 2007). E-flow requirements need to reflect hydrological conditions that support ecological processes and functions. A generalized optimization assessment approach considering a single taxonomic group (e.g. fish) can expose to the risk of adverse effects on other components of the ecosystem and lead to unpredictable ecological results both at the short and long-term scales (Acreman et al., 2014; Tonkin et al., 2020). Thus, the acknowledgment of the role of each biological group in the ecological framework results "fundamental to the maintenance of diverse and resilient communities into the future" (Tonkin et al., 2020). In the frame of the study, despite not explicitly considering existing direct and indirect relationships among the considered biological groups, we simultaneously included hydrological conditions of different biological groups to define the e-flow requirements in the Pas River throughout the year (Figure 8). In this regard, we encompassed three biological groups (Biological Group 1, 2 and 3) within the relevant levels of the trophic network of the ecosystems (from primary producers to apex predators). The process of e-flow requirement (R) definition (i.e. hydrological conditions for the biological groups) was based on the output of a workshop with a group of experts in the fields of hydrology, eco-hydrology, and freshwater biology from the IHCantabria (Santander, Spain). The e-flow requirements considered in this study are not absolute, meaning that they can be refined based on the dominant situation and idiosyncrasy of each watershed (establishing definitive values was out of the scope of this work). A summary of the requirements is shown in Table 9.

Biological Group 1 included fish species. Fish species are top predators and might represent an economic source for the local population in the region, associated with recreational angling (Hunt et al., 2017). Life cues of fish species are closely linked with the magnitude and timing of the distinct flow regimes. Despite different fish species have specific adaptation strategies and hence can tolerate the modification of either magnitude or timing of river flows to a certain extent, modification of flows during key stages of life-cycle (e.g. migration, spawning, hatching, recruitment; Gibbins et al., 2008; McMichael et al., 2005; Tetzlaff et al., 2008; Trotter, 2016; von Schiller et al., 2017) could compromise population structure (Jonsson et al., 2011) or even increase the extinction risk (Bradford & Heinonen, 2008; Saltveit et al., 2019). The hydrological requirements (R1-R4) for Biological Group 1 aimed at the maintenance of certain flow conditions for cues (e.g. spawning or feeding) for the majority of the year (especially during dry periods) and at ensuring the occurrence of peak flows (e.g. for migration). Particularly related to the September period (characterized by reduced discharge), we exploited the synergy (and avoid algorithm conflicts) with

R5 and R6 (described below) to ensure both survival and migration of the fish, which provided low flows and peak flows, respectively, during the month of September.

Group 2 considers aquatic macroinvertebrates. Aquatic macroinvertebrates' community composition is highly diverse (e.g. grazer, shredders, predators; (Wallace & Webster, 1996) and each community exhibits different responses to hydrological gradients and flow frequency (Booker et al., 2015; Chen & Olden, 2018; Dollar et al., 2007). Since additional experimental evidence is needed to define the accurate requirement of each taxonomic group, we considered the highest taxa occurrence probability (the underlying rationale was based on the Intermediate Disturbance Hypothesis (Osman, 2015) as an indicator for the e-flow requirement for this group. The hydrological requirement (R5) for Biological Group 2 considered the occurrence of high flow conditions to reduce the alteration from flow diversion (e.g. flow magnitude and variability).

Biological Group 3 considered for the optimization assessment refers to primary producers (PPs). PPs have a role in defining the presence of the other two groups (i.e. Biological Group 1 and 2) because of their position at the base of the food-web (Bowden et al., 2017). PPs encompass a variety of taxonomic groups (from diatoms imbibed within the biofilm to macrophytes) that respond differently to changing hydrological patterns. The opportunistic response of PPs to variation in hydrological conditions defines the establishment of specific groups based on flow regime characteristics. We assumed that establishment success (i.e. ability to develop cover) is supported by a minimum flow during the dry period and hence defined the hydrological requirement (R6) in the targeted period (April to September).

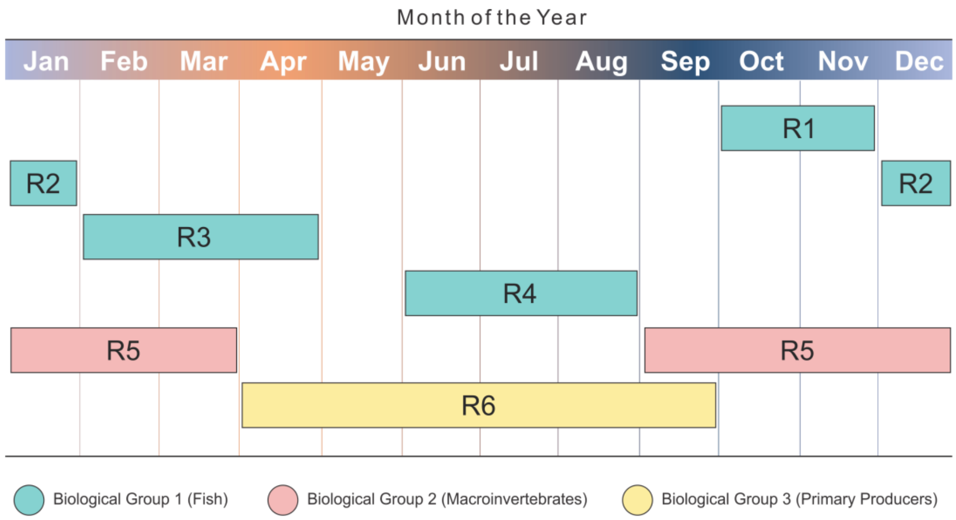


Figure 8 **Annual distributions of e-flow requirements defined for the Pas River.** Each requirement has been translated into the ecological objectives within the optimization model for water diversion.

Table 9 **E-flow requirements considered in this study.** The requirements define hydrological conditions to be conserved in the river during the daily diversion operations throughout the year. Q95-Q75 is the flow value that is exceeded 95% and 75% of the time, respectively; FRE3 is the flow value that exceeds three times the median flow.

Target group	Requirement	Definition
Biological Group 1	R1	Q95 flow – full period
	R2	FRE3 flow – 21 days (consequent)
	R3	Q95 flow – 45 days (consequent)
	R4	Q95 flow – full period
Biological Group 2	R5	Q75 flow – 5 events
Biological Group 3	R6	10% average yearly flow – 70 days (consequent)

3.3.4 Definition of the Pas River optimization problem

To identify the highest water supply sustainability in the river basin, the magnitude and timing of river water diversion operations need to be optimized to comply with the considered e-flow requirements. Hence, the latter generally constrains the availability of water for human consumption. Constrained multi-objective optimization is an optimization method based on the search for feasible solutions that directly limit the search space (Srinivas, 2019). This method is frequently applied in real-world settings of structural and operational optimization assessments for water regulation assets (Alais et al., 2017; Chang et al., 2010). An approach for constrained optimization is represented by the penalty-based approach; it allows transforming the problem into an 'unconstrained' one – penalty (constraint) is incorporated into the objective function to reduce the fitness of the function based on the degree of the specified violation. The penalty-based approach particularly suits optimization assessments considering a high number of limiting conditions. Moreover, it can be easily implemented with evolutionary/genetic algorithms (Bustince et al., 2018; Jadaan et al., 2009; Yeniay, 2005). In this study, the maximization of the conservation potential of the hydrological conditions for the biological groups and the satisfaction of the yearly municipal water volume demand are considered in the formulation of the problem functions as conflicting objectives. For each e-flow requirement objective, a penalty score method based on the characteristics of the requirement was defined and incorporated into the objective function. The calculation of the penalty score and the objective function varied based on the type of requirement. The general structure of penalty score and objective function calculation process is shown in Figure 9, while the detailed functions used in the optimization problem are available in Supplementary Material to this paper. Considering the specific case of river flow diversion, the requirements have been specified as thresholds for the river flow component modification. A flow condition above the threshold will be always favored by the algorithm, while a hydrological condition below the defined threshold will be penalized based on the degree of the violation. Each function output has been normalized based on the characteristics of each requirement, with scaling between zero (i.e. the best outcome) and one (i.e. the worst one).

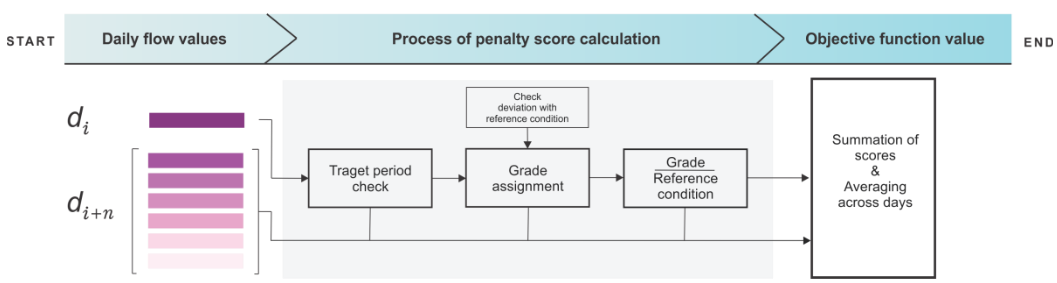


Figure 9 **General structure of the calculation process for the penalty score and objective function** ($\boldsymbol{d_i}$ and $\boldsymbol{d_{i+n}}$ indicate a day $\boldsymbol{i}$ of the year starting from January 1st).

3.3.5 Hydrological data

The developed optimization assessment used input hydrological data describing the river discharge for the Pas River basin. The simulated time-series at the daily scale resolution (for the period 1980-2006) for the two diversion points (DP1 and DP2) was generated by manipulating two datasets provided by the

IHCantabria. The first dataset of discharge values developed by García et al., (2008) for the Pas catchment by using the updated version of the rainfall-runoff model (HEC-HMS; Scharffenberg, 2010). This dataset was available only for certain points along the river network at daily resolution. The second dataset contained discharge data extracted from the Spanish national repository and was processed with the SIMPA GRASS-based tool (Álvarez et al., 2004), available for each 500 m section of the river network at monthly resolution. To obtain the aforementioned time-series at the desired temporal resolution format (i.e. the daily scale resolution) used in this study, a conversion factor (i.e. flow magnitude coefficient) for the target river segments (in correspondence with DP1 and DP2) was first extracted from monthly scale data (SIMPA tool) and successively multiplied to the daily flow data (HEC-HMS model).

3.3.6 Optimization scenarios

Scenario development aimed to capture lower than average, average, and higher than average hydrological conditions at the considered diversion points (DP1 and DP2) to increase produced information uptake and fostering discussion about management practices in the Pas River. With this purpose, hydrological year-based scenarios namely dry, normal, and wet, were developed to explore optimization outcomes at different hydrological conditions (see Figure 10). Firstly, each year in the record (1980-2006) was sorted based on its average yearly discharge value (the years 1980 and 2006 were discarded as only full-data years were considered), and a three-tiered statistical breakpoint classification has been applied. Each class contained 33% of the data with higher, medium, and lower average yearly discharge values. Lastly, daily averages have been recalculated among years of the same class to obtain the three sample hydrographs used in this study. The daily values of each hydrological time series (at the daily time-step

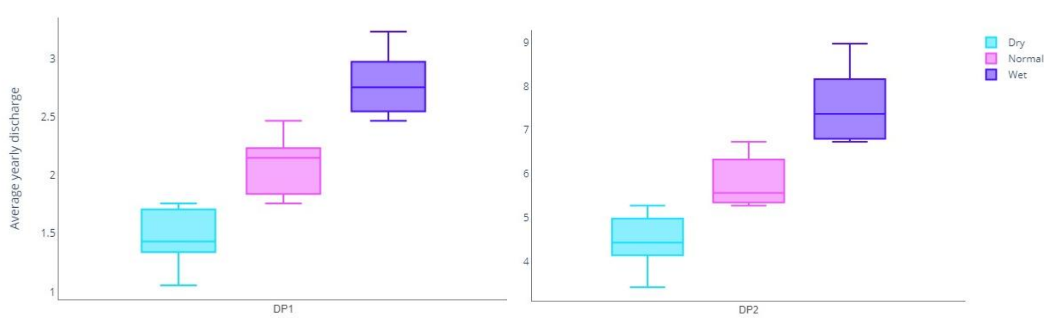


Figure 4 **Average yearly discharge values (in m3/s) for the considered scenarios (dry, normal and wet) for the two diversion points DP1 and DP2.** The upper and lower fences represent the max and min discharge vales, the edges of the box represent the upper and lower quartiles, and the line inside the box is the median.

starting from January, 1st to December, 31st) under each considered scenario for both DP1 and DP2 is available in Figure S1 in the Supplementary Materials to this paper.

Despite real-world daily river discharge can greatly fluctuate around the daily average discharge values within each scenario that we considered in the optimization assessment, this is mostly due to less predictable (in the long term) factors as precipitation and temperature. Forecasting the exact discharge value occurring at a specific day with the aim of planning daily diversion is still challenging. A simple approach to tackle this issue is the consideration of representative discharge patterns throughout the year. In this study, the produced hydrological scenarios (or hydrographs) are intended only a basis for exploration and discussion about potential decisions and management practices rather than absolute discharge values. Hence, a key assumption underlying the input hydrological data (hydrographs in Figure S1 in the Supplementary Materials) was that it serves as a representative 'sample' of the current hydrological conditions at the daily scale for each considered scenario.

3.3.7 Evolutionary optimization algorithm and framework

To solve the presented non-linear optimization problem for the Pas River we applied the state-of-art of evolutionary algorithm NSGA-III (Deb & Jain, 2014) by exploiting the *Pymoo* – Multi-objective optimization in Python - framework version 0.4.1 (Blank & Deb, 2020a). To track the convergence towards the optimal solutions we used a recently developed running metric indicator. Although the hyper-volume convergence metric is a widely employed technique, it requires the knowledge of the "true Pareto front" which is not always available (see Blank & Deb, 2020a); the aforementioned running metric indicator uses extreme points and the information of the non-dominated solution retrieved at each generation to define the convergence evolution (for in-depth explanation see Blank et al., 2019; Blank & Deb, 2020b). The structure of the optimization module applied to the defined optimization assessment problem for the Pas River basin simulation runs is shown in Figure 11. The Pymoo module is then linked with two additional modules: a module that extracts the input hydrological indices (i.e. Q75, Q95, FRE3 and AYF – average yearly flow); and a scenario module that processes the hydrological record and provides input hydrological conditions. The algorithm was parametrized with a population size of 100 individuals and run for 1000 generations. The running metric was set on a 50-generation step.

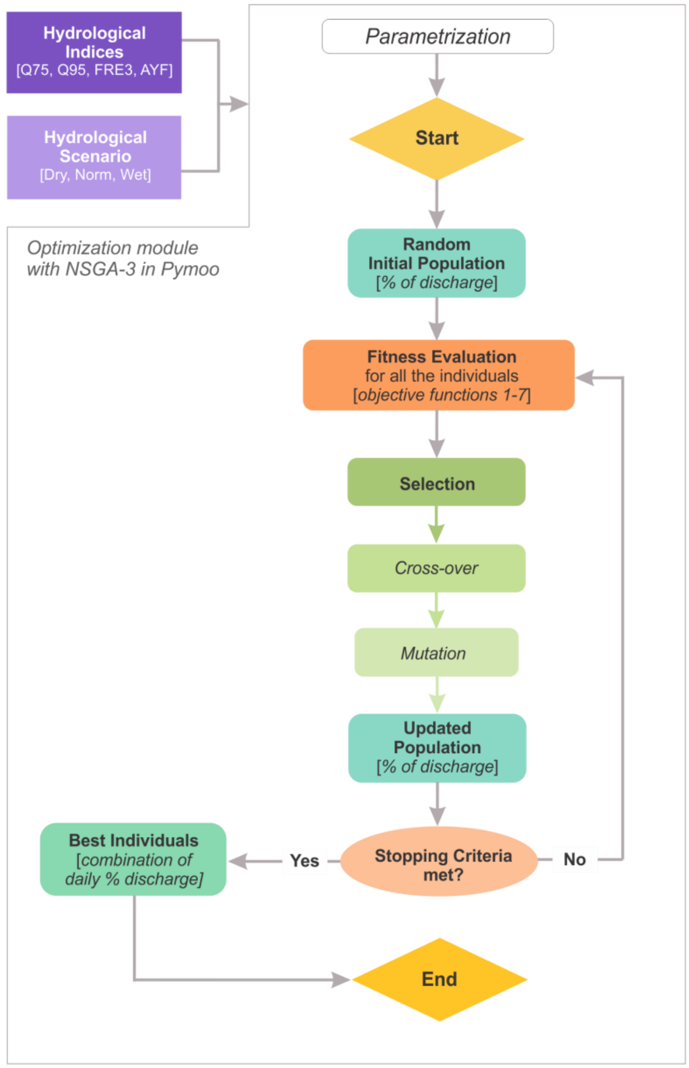
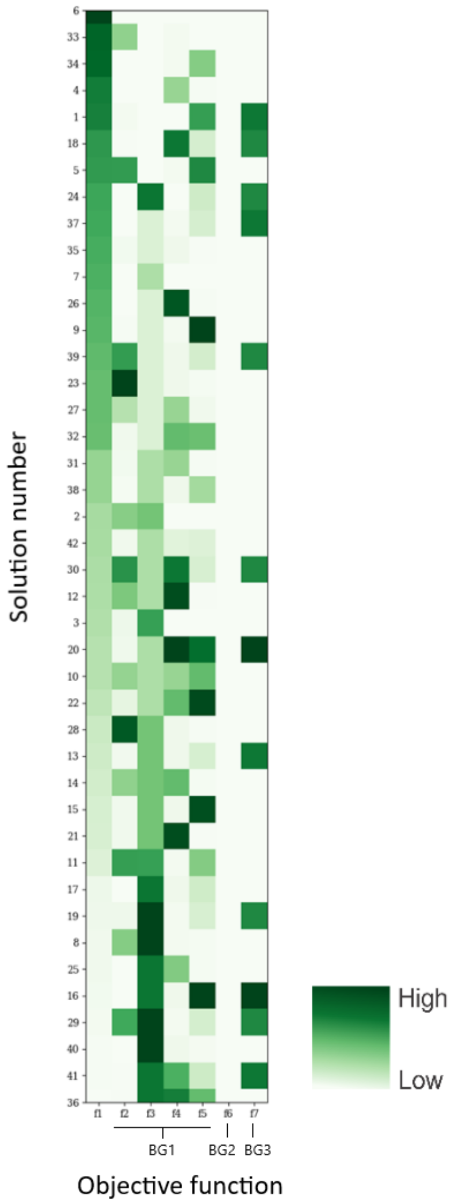


Figure 5 **Optimization problem structure employed to the Pas River.** The main box shows the module structure of the Non-Sorted Genetic Algorithm-3 (NSGA-3) in Pymoo – multi-objective optimization in Python. Two external modules, Hydrological Scenario and Hydrological Indices, calculate the hydrological scenarios to be inputted into the Pymoo module and the hydrological variables, respectively.

3.4. Results

Providing sufficient water for consumptive use (e.g. municipal, industrial) was the primary objective of the water management optimization problem developed for the Pas River case study. Simulation results for the different diversion points (i.e. DP1 and DP2) showed that the overall annual water demand for municipal use (calculated in Hm3/y) set as demand objective was fulfilled under all the considered scenarios (see Tables S1 and S2 in the Supplementary Materials). The total annual water volume for municipal use increased with the increased availability of river discharge and was at its highest value under the wet scenario conditions. On the other hand, e-flow requirement objectives (i.e. R1-R6) scores showed very small deviations (in their normalized values) to the test runs (reference scores of the undisturbed hydrograph; see Tables S3-S8 in the Supplementary Materials). Test scores different from zero indicate the original input hydrological conditions not allowing requirement meeting. This means that additional pressure on the target Biological Groups already exists under some natural hydrological variability from one year to another. The most noteworthy changes are related to the R2 objective scores, which showed a linear trade-off with the municipal water supply objective (see Figure 12 as an example, other results available at https://doi.org/10.6084/m9.figshare.14230553; ; Derepasko, Peñas, et al., 2021). For the remaining optimization objectives, the trade-off pattern was characterized by a non-homogeneous behavior to the supply objective gradient pattern. This can be due to the more strict nature of the penalty requirement assigned to the objective.



It is important to note that the reference e-flow requirement scores (R1-R6) for the natural (or undisturbed) river flow showed that in few cases the hydrological conditions for the selected Biological Groups were sub-optimal (i.e. higher than zero) also before the trading of water with municipal diversion (see Tables S3-S4-S5 and S6-S7-S8 in the Supplementary Materials). This means that the reference natural discharge conditions used could have in some cases contributed to increasing the score for the Biological Groups.

Results also indicate that the daily availability of water for abstraction varied throughout the year; what we explored from model results was this day-to-day variability in the water quantity for municipal diversion defined as optimized discharge (OD). To reduce uncertainty in the OD range values, the optimization problem was run under three different hydrological scenarios (dry, normal, and wet) and ten independent times for each diversion point and each

Figure 6 **Heat map of the objective functions**. Heatmap showing the sorted normalized objective functions scores [on the y-axis] for the e-flow requirements (BG1=Biological Group 1; BG2=Biological Group 2; BG3=Biological Group 3) in relation to the municipal water supply objective (f1) [on the x-axis]. Tiles hue indicates the score (dark green=high/best scores; light green=low/worst scores). Presented result is for run #1 for DP1, dry scenario.

hydrological scenario. Each model run outputted a batch of day-to-day OD annual series when run for a specific scenario. Results indicate that despite the stochastic nature of the genetic algorithm (as it uses random input values of the potential optimized diversion volumes), the prevailing pattern of the optimized diversion volumes repeats across the different runs for the same scenario (see as example Figure 13 which depicts the outputs for DP1 under the dry scenario).

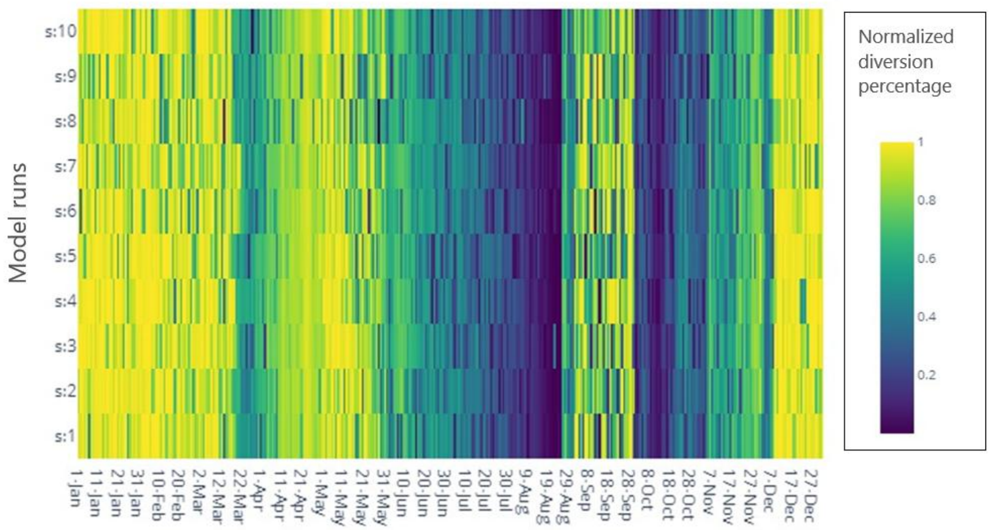


Figure 7 **Optimization runs.** Comparison of the results for each run of the optimization model showing the pattern of the normalized average daily diversion percentage values (expressed as the daily percentage of the natural daily discharge). Yellow (1) tiles correspond with the highest daily percentage, whereas blue (0) tiles correspond with the lowest optimal daily diversion. Presented results are for the DP1 under the dry scenario.

The shades of the tiles are in agreement for the majority of the days of the year meaning that the algorithm was able to converge at each run to similar solutions, and hence the model identified a prevailing trend of optimal solutions (i.e. the daily optimal amount of water for diversion) distribution throughout the different model runs. The results of the time window from the end of August to the beginning of October are more heterogeneous (i.e. the daily OD value changes significantly between each run). This indicates a greater variability of the average daily diversion values identified by the model. Similar patterns across the model runs emerged for the other diversion point and scenarios (see Figures S2-S3, Supplementary Materials).

To provide a greater understandability and to explore the obtained results we averaged the batch of daily diversion percentages for each scenario to obtain the mean daily percentages of the natural discharge (%OD), as shown in Figure 14 for DP1 under the dry scenario. The %OD (optimized discharge expressed as a percentage share of the natural flow) changes significantly daily. Results across the diversion points (see

Supplementary Materials, Figures S4-S5) show that for the majority of the year over 50% of the daily river discharge was not required for the selected environmental criteria. The highest %OD volumes are more evident in the first half of the year (Jan-June) to the second half: this quantity decreases as river natural flow declines because of the low flow season. Larger variability in abstraction shares characterizes the months from September to November which can be attributed to the variability in precipitation distribution upstream causing peaks in the river discharge in correspondence with the diversion points.

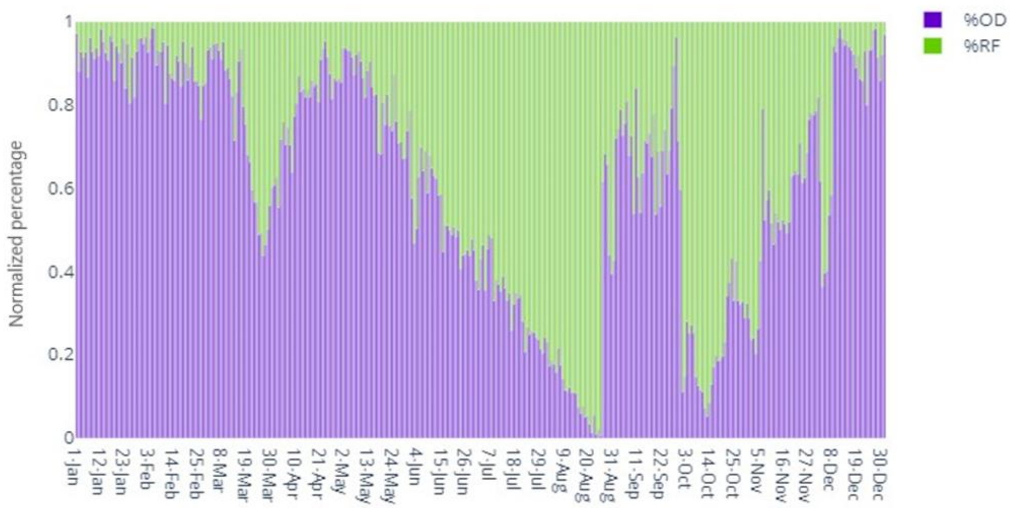


Figure 8 **Reference flow and optimized flow.** Comparison between the residual percentage of natural daily flow (green - %RF) remains in the river and the average daily discharge optimized for diversion (purple - %OD]). The diverted discharge is calculated as a daily average for all the 10 runs of the model. Presented results are for the DP1 under the dry scenario.

By considering the results from the analysis of the individual simulations, we compared the averaged results to the natural discharge in the river. Given the size of processed information available from simulation runs we summarized all the results in Tables S9-S10 (Supplementary Materials). To understand the trends throughout the year we plotted the value of the unaltered river flow with the flow portion optimized for diversion (see Figure 15 as an example for the DP1 under the dry scenario; complete results are available in Figures S6-S7 in the Supplementary Materials). The OD mainly follows the profile of the natural discharge, which corresponds with the upper edge of the line, for the greatest part of the year. Thicker lines, and hence a greater quantity of water that should remain in the river, concentrate in the driest days of the year. This is plausible due to the required objectives of maintenance of base flows. It is important to note that days where the width of the line is thinner, indicate that the optimized discharge almost matches with the totality of the natural discharge. This is because the lower edge represents the ideal amount of water that can be abstracted. It represents an indication about the greatest water amount

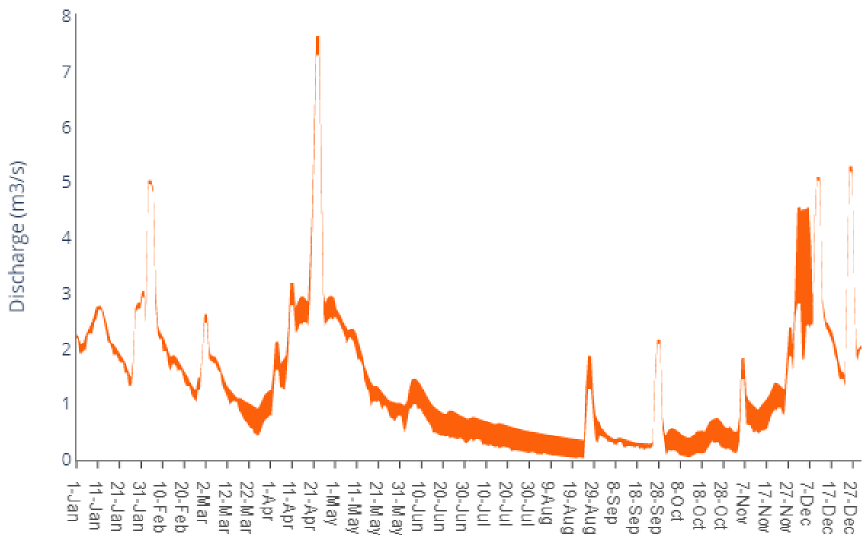


Figure 9 **Gap between optimized and natural flow.** Flow series showing the magnitude of gap between the daily optimized diverted discharges with respect to the natural discharge for the DP1 under the dry scenario. Greater thickness indicates the highest trade-off between the natural discharge and water for municipal use.

available for daily abstraction being the latter an average of the results across all the runs. The reason for the presence of unmatched discharge (i.e. greater gap) can be related to the specific scenario used (i.e. the representative hydrograph) and hence associated with the hydrological model used to generate the data.

3.5. Discussion

3.5.1 Trade-offs between diversion and biological groups' requirements: Variability in the daily flow available for diversion

Considering water demand fulfillment needs, the optimization of daily flow for diversion evidenced periods of major and minor daily average trade-offs (expressed as the quantity of flow that is available for abstraction against the quantity of flow that should remain in the river), meaning that periods of lower availability of water for diversion are present. Our optimization assessment shows that trade-offs of human water use against the water needed to protect the ecosystem are not manifesting at the annual scale (i.e. modification of the total quantity of water that can be abstracted annually) but rather, the trade-off is more evident at the daily scale. Since the magnitude of this trade-off varies across the solutions found by the algorithm (during each run), the selection of one solution over another is usually required. However, the process of option selection remains a prerogative of the decision-maker as it requires appropriate engagement strategies for management preference elicitation (O'Sullivan et al., 2020). Results presented in this study (as average daily diversion values) allow showing the variance of the daily threshold defining the optimized abstraction throughout the year. Knowledge of these daily trade-off thresholds can serve as guidance for the daily diversion operations throughout the year. They can also guide decisions on the timeframes for planning and revision of the management objectives that will strengthen the overall water management capacity (P. Kumar et al., 2019). Further inclusion of other statistical information (e.g. standard deviation) would be beneficial in supporting the judgment underpinning diversion decisions.

Aiming at reducing alteration of surface water diversion assumes that the input hydrological scenarios (related to an undisturbed hydrograph) fulfill the needs of the ecosystem. In our study, the considered background hydrological conditions (i.e. input scenarios to the optimization model) were not scoring optimally (i.e. zero) for the entire set of objective functions as required by the targeted biological groups. On one hand, this outcome could be related to the type of data and the design of the assessment, it also suggests that climate change impacts leading to more frequent droughts and reduced amounts of rainfall will increase the pressure and hence risk the conservation of the targeted biological groups. Both the climate and geomorphological features (e.g. slope, vegetation type, etc.) influence the local seasonal change in river discharge and can affect, for instance, physio-chemical river properties (Moodley et al., 2016; Sigleo & Frick, 2007). Changes in land use and land cover at the local and regional scale influence the runoff and hydrology (Mirhosseini et al., 2018; Welde & Gebremariam, 2017). This suggests that both objective scores and the magnitude of daily trade-offs can be reduced (i.e. reduced variability in water available for diversion) if additional measures on the local scale are implemented (such as replacing farmlands with forest cover). The consideration within the optimization assessment for adaptive water management of additional hydrological scenarios based on land use/land cover changes would provide insights into alternative water management practices in the face of climate change conditions.

3.5.2 Advantages: The role of simulation conditions for the results

The application of optimization approaches shows several advantages for water management, such as the chance to modify prior conditions (e.g. total demand, daily river flow). This provides the opportunity for foreseeing outcomes of decisions under alternative scenarios improving the decision-making process. In particular, the chance to modify the input hydrological conditions and the defined e-flow requirements is useful to increase the understanding of implications for diversion of alternative water allocations for environmental needs. For example, by increasing the allocation (share of discharge for ecological processes) or including additional biological groups, or any other sort of geomorphological or biogeochemical criteria for the achievement of a “good” ecological status, can identify the best e-flow water management options that have the least implications for water diversion. However, while the role of science for supporting decision-making still faces challenges such as providing greater evidence for flow-ecology knowledge (Stoffels et al., 2018), expanding the e-flow requirements for more species and other components of the ecosystem could improve the chances of achievement of environmental goals. On the other hand, the modification of the reference hydrological conditions (input hydrograph) by considering the same ecological requirements could increase the resolution of the daily diversion threshold under specific conditions. Overall, this strengthens the reliability of daily diverted volumes identified by the model.

Another advantage of the employment of optimization approaches for fostering the adoption of adaptive water management strategies is represented by the chance of incorporating e-flow requirements within management decision assessment regardless of their type (i.e. as minimum flows, natural flows, indicators of hydrologic alteration). Moreover, environmental data are not always readily available in a format suitable for decision-making. E-flows can be expressed both as objectives or constraints depending on the modeling capacity and ability (Derepasko, Guillaume, et al., 2021). However, each e-flow modeling approach used within the optimization assessment would also require an appropriate results communication strategy (Pollino et al., 2017).

Despite models have a great potential for socio-ecological research (Schlüter et al., 2019), each modeling exercise requires prior conditions (e.g. scenarios) to be stated in the model, and the results remain highly linked with those conditions. Optimization assessment for water management is no exception, but optimization results exploration offers ground for discussion of decisions and is meant to convey information useful for the decision-making process (A. C. Horne, Kaur, Szemis, Costa, Nathan, Angus Webb, et al., 2018). This particularly suits the adaptive process.

3.5.3 Limitations: Sources of uncertainty defining the optimal diversion

Systemic, data-related, and epistemic uncertainties affect socio-environmental modeling (Lowe et al., 2017). We identified the systemic uncertainty to be the one related to the search approach (e.g. stochastic) and the number of model runs. Not many studies addressed the question of the number of simulation runs and the best choice is represented by the "minimum number of runs" (Ritter et al., 2011), especially when simulations are particularly expensive. While ten runs for each hydrological scenario allowed defining the prevailing annual pattern of water diversion in our study, we believe that a further increase of simulation runs especially in the case of heuristic methods as genetic algorithms would allow reducing the uncertainty of results, increasing the probability of ecological objectives achievement.

Data-related uncertainty is related to both present condition outcomes and future scenarios. In our study, in the absence of real flow data, simulation data lead to the application of a precautionary approach that considered the abstraction of the lowest amount of flow that can be diverted daily. To a certain extent, this could represent the best available strategy for resource management. However, knowledge of the extent of the “safe abstraction range” and the associated probability would contribute to enhancing decision-making especially to climate change-induced changes in the hydrological behavior of the river flow (Schneider et al., 2013) which are difficult to quantify and track. Methods that could address the unpredictability of multiple flow conditions on a daily scale such as the Monte Carlo sampling (Byrne, 2013) could be used to generate many input hydrological conditions on which to run the optimization algorithm. However, this will inevitably increase post-processing effort (e.g. related to data volume).

Lastly, because of the complexity of the water management problem and optimization problem, the use of expert opinions and knowledge is both a precious source of information in different situations (e.g. urgency of implementation of management actions, limited evidence) and a source of uncertainty (epistemic) linked with the subjective view of the knowledge (Krueger et al., 2012). In the case of our study, epistemic uncertainty relates to both optimization assessment design and expert knowledge. In the first case, this can be improved by creating alternative assessment designs (e.g. changing objectives, solution search methods, scales (Derepasko, Guillaume, et al., 2021; Rolls et al., 2018); and by expanding our knowledge of eco-hydrological relationships and ecosystem needs or by extending the pool of experts enquired in the second. Additionally, participatory approaches for the definition of objectives and optimal solutions could support the identification of the appropriate scales and design for the management problem (Wicki et al., 2021).

3.5.4 Implications of the results for the diversion planning and the adaptive management approach in the Pas River

Optimization can be used to translate knowledge of flow conditions that support environmental processes into information used by decision-makers. This information then supports strategies and maintenance of long-term goals for river management (O’Donnell & Garrick, 2017) under a range of possible hydrological circumstances (i.e. below normal, normal, or above-normal conditions). The great variability in the amount of flow throughout the year that can be diverted daily for consumptive use suggests that the definition of the monthly targets for municipal consumption (in Hm^3) would be a much more appropriate management objective compared to the targeted annual water allocation volumes for the local scale. The main reason is that naturally, the river does not offer stable hydrological conditions for diversion throughout the year at different locations. Reducing the time window of consumptive allocation validity could incorporate these circumstances, and prevent overexploitation. River water can be diverted during periods of greater availability and temporarily stored for the next period but water collection and storage systems would eventually require investments and additional costs (Young, 2014).

Active water management is a management approach that calls for ongoing decisions concerning the water required for environmental needs (see Doolan et al., 2017; A. C. Horne, Kaur, Szemis, Costa, Nathan, Webb, et al., 2018) while aiming for long-term management goals (i.e. good ecological status and human development; A. C. Horne, Kaur, Szemis, Costa, Nathan, Webb, et al., 2018). This approach suits the case of regulated rivers such as the Pas River in which at least certain flow conditions need to be considered as the rightful reserve for the ecological processes. This means that certain flexibility of design of the environmental objectives within the optimization assessment should consider thresholds and parameters that can be adjusted based on ongoing monitoring outcomes. The marked difference in natural flow conditions, and consequently abstraction conditions, between seasons, suggests that the seasonal scale could potentially represent the minimum time scale over which active management should be implemented. For example, fish species respond to hydrological cues linked with the seasonal variation of flow. When considering water requirement objectives for fish biological groups, evaluation of the achievement of the expected phenological event from monitoring results is needed to adjust the threshold or the timespan for the environmental water allocation for the next phenological period. This would ensure species conservation and ecological restoration. Moreover, by increasing the scale of the assessment (i.e. expand the analysis to multiple reaches or the entire basin) more detailed information can arise and management planning can be extended over larger portions of the river. However, while optimization allows assessment of both advantages and disadvantages of specific management decisions, clear links between monitoring strategy and management goals still need to be stated before the assessment phase to ensure the success of the adaptive management approach (Adams & Van Niekerk, 2020; Stein et al., 2021).

Overall, the optimization assessment proposed in this paper represents an opportunity to investigate what implications arise from the incorporation of ecological needs within a diversion plan. Results should not be considered as absolute, but they rather serve to highlight that trade-offs in water availability are more linked to the daily scale (i.e. daily diversion) than the annual scale (overall volume diverted in a year). Increased chances of results uptake by the decision and policymakers would need an extended assessment on the basin-scale and multiple simulations with sensitivity analyses. Furthermore, this study showed an approach of e-flow requirements definition within the optimization assessment to extract information useful for the promotion of an adaptive management process. Besides, as the provision of e-flows is a means to restore the benefits of naturally flowing rivers, the optimization assessments can also match the exploration of actions for the eventual restoration of ideal ecological conditions. In this case, the advancement of the available eco-hydrological knowledge to be used to build the optimization model would significantly improve the chances of restoring natural conditions while meeting supply objectives. The proposed assessment can be applied to other basins and locations but would inevitably need the adjustment of e-flow requirements (i.e. thresholds and parameters) to match local ecosystem needs. However, regardless of its usefulness in supporting the adaptive process, the lack of proper link definition between the e-flow requirements and the subsequent monitoring stage within an optimization assessment can jeopardize the success of an adaptive management approach (Webb, Watts, et al., 2017).

3.6. Conclusions

This paper illustrates how an optimization assessment offers the opportunity for designing e-flow requirements in a format suitable for informing water management and at the same time offers support for the commitment to all the stages of the Adaptive Water Management Cycle (AWMC). We demonstrated that the optimization process structure (e.g. limiting conditions definitions and objectives) matches the presented approach applied for e-flow requirements incorporation. In particular, the presented approach suits the need to anticipate management outcomes by exploiting the hydrological thresholds as limiting conditions for river water diversion. On one hand, the advantages of the optimization assessment as an instrument for mediating the incorporation of e-flows lie in the opportunity of tailoring e-flow requirements both to the available data and modeling capability. On the other hand, the need to pre-define conditions (e.g., input hydrological information, supply volume) can expose results to different levels of uncertainty. Lastly, we identified few opportunities for the improvement of the management approach in the case study area: the reduction of the allocation volume temporal window during diversion planning such as by setting monthly caps on water allocation for consumptive use based on seasonally averaged river discharge would allow incorporating natural flow variability (for ecosystem needs) and prevent overexploitation during periods of scarce flows. Future applications of the optimization assessment in support of Adaptive Water Management would benefit from an improved characterization of the reference river flow conditions through the inclusion of approaches to reduce uncertainty (e.g. employment of input data-sampling techniques), the incorporation of alternative land-use/land cover information and climate change scenarios. Moreover, stronger links between considered e-flow requirements and monitoring planning would push the adaptive process further towards the closing of the AWMC. Overall, this would reduce the risk of failure of e-flow requirements incorporation in the management program and contribute to improving management actions outcomes.

Supplementary Materials:
The following are available online at https://www.mdpi.com/article/10.3390/w13091281/s1, *Figure S1:* Hydrological time series used as representative discharge scenarios for the considered diversion points (DP1 and DP2); *Figure S2:* Combination of the average daily diversion percentages with respect to the natural discharge normalized to 0-1 range for each single run of the model ('s1-s10') under the same scenario; *Figure S3:* Combination of the average daily diversion percentages with respect to the natural discharge normalized to 0-1 range for each single run of the model ('s1-s10') under the same scenario; *Figure S4:* Barchart showing the normalized fraction (expressed in %) of discharge that has been optimized for abstraction (purple 'OD' bars) with respect to the natural flow (green 'RF' bars) at the daily scale (results for DP1 under dry (a), normal (b) and wet (c) scenarios; *Figure S5:* Barchart showing the normalized fraction (expressed in %) of discharge that has been optimized for abstraction (purple 'OD' bars) with respect to the natural flow (green 'RF' bars) at the daily scale (results for DP2 under dry (a), normal (b) and wet (c) scenarios; *Figure S6*: Flow series showing the magnitude of gap between the daily optimized diverted discharges in m3/s with respect to the natural discharge (results for DP1 under dry (a), normal (b) and wet (c) scenarios); *Figure S7*: Flow series showing the magnitude of gap between the daily optimized diverted discharges in m3/s with respect to the natural discharge (results for DP2 under dry (a), normal (b) and wet (c) scenarios); *Table S1:* Average objective function score (municipal water demand), for each simulation run (1-10) (results for the DP1 under dry, normal and wet scenarios); *Table S2*: Average objective function score (municipal water demand), for each simulation run (1-10) (results for the DP2 under dry, normal and wet scenarios); *Tables S3-S4-S5:* Average objective function scores (R1-R6), for each simulation run (1-10) (results for the DP1 under dry, normal and wet scenarios); *Tables S6-S7-S8:* Average objective function scores (R1-R6), for each simulation run (1-10) (results for the DP2 under dry, normal and wet scenarios); *Table S9*: Comparison of average natural discharge values under different scenarios and the optimized discharge thresholds (results for DP1 for sub-normal (dry), normal and above-normal (wet) hydrological conditions); *Table S10*: Comparison of average natural discharge values under different scenarios and the optimized discharge thresholds (results for DP2 for sub-normal (dry), normal and above-normal (wet) hydrological conditions).

4. *Towards adaptive water management — Optimizing river water diversion at the basin scale under future environmental conditions*


water

Article

Towards Adaptive Water Management—Optimizing River Water Diversion at the Basin Scale under Future Environmental Conditions

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References to Supplementary Materials can be found in *Appendix C* attached to this thesis.

4.1. Summary (abstract)

The degree of success of river water diversion-planning decisions is affected by uncertain environmental conditions. The adaptive water management framework incorporates this uncertainty at all stages of management. While the most effective form of adaptive management requires an experimental comparison of practices, the use of optimization modeling is convenient for conducting exploratory simulations to evaluate the spatiotemporal implications of current water diversion management decisions under future environmental changes. We demonstrated such an explorative modeling approach by assessing river water availability for diversion in a river basin in Northern Spain under two future environmental scenarios that combined climate and land use change. An evolutionary optimization method was applied to identify and reduce trade-offs with Supporting Ecosystem Services linked to environmental flow requirements for relevant local freshwater species. The results showed that seasonal shifts and spatial heterogeneity of diversion volumes are the main challenges for the future diversion management of the Pas River. Basin-scale diversion management should take into account the seasonal planning horizon and the setting of tailored diversion targets at the local level to promote the implementation of adaptive management. The presented assessment can help with the strategic placement of diversion points and timing of withdrawals, but it also provides a deeper insight into how optimization can support decision-making in managing water diversion under uncertain future environmental conditions.

4.2. Introduction

The "natural flow paradigm" (N. Poff et al., 1997) is acknowledged as the basic concept for a thriving river ecosystem, however recognizing that certain key flow components must be conserved presents a unique challenge for managing river water resources sustainably. Currently, the challenges related to water resource management and its allocation are increasing each year globally due to several pressures, such as climate change and population growth, but also due to trade and energy crises, food production, water scarcity, and pandemics, to name a few (Alamanos & Koundouri, 2023; Grison et al., 2023). In Europe, there are significant differences between countries in terms of both the intensity of the pressures mentioned above, especially climate change extremes (Moghim et al., 2022), and the degree of effectiveness of the water management strategies employed (Ziolkowska & Ziolkowski, 2016). Enhancing water management efficiency requires anticipating the consequences of management outcomes and future environmental circumstances. To achieve this, we need advanced modeling approaches that can assess and guide decision-making in current and future scenarios.

The water management encompasses a range of interventions aimed at regulating the river system, which involves constructing dams to control water flow or diverting river water. Through water intakes, water diversion alters the flow regime of the river (i.e., its magnitude, seasonality, and variability) (Stewardson et al., 2017), potentially compromising the integrity and functionality of the river ecosystem and the services it provides (Alan Yeakley et al., 2016; Ferreira et al., 2022; Gilvear et al., 2017; Jähnig et al., 2022; Rolls & Bond, 2017; Rosero-López et al., 2020; Watz et al., 2022). The concept of environmental or ecological flows (e-flows) is recognized as a valuable instrument for achieving sustainable water resource management or sustainable water diversion as it considers the 'quantity, quality and timing of flows that are needed to sustain the ecosystem' (Arthington, 2012; Gilvear et al., 2017). Ongoing intensification of environmental changes related to climate and land use leads to uncertainty in the timing and location of river flow components alteration manifestation (i.e., e-flows). As a consequence, modeling approaches providing means for exploring spatiotemporal implications of current water diversion management decisions under future environmental changes could provide water managers with reliable information for strategic water diversion planning (Fowler et al., 2022; Horne et al., 2022; John et al., 2020; Judd et al., 2022; Lowe et al., 2017).

The water diversion management strategies implemented so far are, to some extent, supported by the incorporation of the Integrated Water Resource Management (IWRM) concept (Delavari Edalat & Abdi, 2018; Pahl-Wostl, Kabat, et al., 2008). While the latter remains a cornerstone of water management approaches, it has evolved into a more articulated paradigm: the "adaptive" water management based on the "learning-by-doing" cycle, which better meets the need to deal with the increasing uncertainty associated with future changes and management outcomes (Allan & Watts, 2018; Delavari Edalat & Abdi, 2018; Pahl-Wostl et al., 2012; Pahl-Wostl, Kabat, et al., 2008; Sendzimir et al., 2007). While a management strategy or decision is assessed in the outer loop, uncertainty within the cycle is addressed through inner loops of minor adjustments to the management approach as functional outcomes become available (for a detailed explanation, see: Horne et al., 2022; Webb, Watts, et al., 2017). However, this inherently implies that adaptive management of water resources involves implementing a particular management strategy and repeatedly adjusting it to achieve the desired success or management objective. Indeed, "the most effective form of adaptive management employs management programs that are designed to experimentally compare selected policies or practices by evaluating alternative hypotheses about the system being managed" (Allan & Curtis, 2005; Pahl-Wostl, 2006). However, comparing policies and practices in the actual world is time and resource-consuming and not very cost-effective, making it highly unlikely. Nevertheless, using models that consider real-world conditions to conduct experimental simulations allows these hypotheses to be tested before implementation takes place. Moreover, this approach enables the identification of space and time dimensions that would enable the implementation of an adaptive management cycle.

A significant number of modeling approaches to predict water management outcomes under uncertainty are nowadays available (Badham et al., 2019; Borgomeo, 2022; Candido et al., 2022; Kirchner et al., 2021; Lowe et al., 2017; Refsgaard et al., 2007). Modeling and simulating are generally subject to uncertainties arising from various sources (see Lowe et al., 2017; Refsgaard et al., 2007). One way to tackle the uncertainty associated with water diversion management outcomes is to evaluate management decisions under different environmental change scenarios. Optimization modeling is a versatile tool for this purpose and has been used extensively to model water management problems (Derepasko, Guillaume, et al., 2021; A. Horne et al., 2016). It represents a prescriptive type of modeling (Candido et al., 2022) and is flexible in terms of the type, size, and scale of the problem but does not require extensive training compared to using software. Ultimately, optimization is suitable for analyzing solutions to water management problems through the employment of system perceptions (i.e., real-world system representation as we perceive it to be), preferences (i.e., preferred solutions based on personal interests and priorities), and scenarios (i.e., plausible real-world conditions) (Derepasko, Guillaume, et al., 2021; Derepasko, Peñas, et al., 2021).

Optimization has been used in studies assessing changes in riparian areas at the river network segment scale (Witing et al., 2022); however, the authors are not aware that an optimization assessment has been carried out for river water diversion at each segment of a river basin network considering future environmental changes. To bridge this gap, in this paper, we perform an optimization assessment for the Pas River basin in Northern Spain. Through this study, we aim to showcase the applicability of the optimization approach at the river network scale with river segment resolution. More specifically, the modeling exercise aims to (1) design an optimization model for river flow diversion and ecosystem services (ES) supply capacity at the basin scale under climate and land use change scenarios, (2) identify spatial and temporal patterns in the optimization results, and (3) provide recommendations for basin-scale water diversion management and modeling to relevant experts. The presented approach is designed to consider local hydrological conditions and plausible future scenarios while addressing the environmental flow requirements of key biological groups (i.e., Supporting ES). The assessment performed with the presented approach aims to identify spatiotemporal scales that increase the robustness of current diversion management decisions to climate and land use changes, with the ultimate goal of facilitating the identification of scales that enable adaptive management.

The chapter is organized as follows: Section 4.3 introduces the case study and the framework of the optimization problem (sections 4.3.1 and 4.3.2) through the stages of problem perception and problem definition. A suite of representative results is presented in Section 4.4. Section 4.5 discusses the spatial and temporal scales of change. Based on the explorative modeling assessment we provide recommendations for both management and modeling (Section 4.6).

Using the case application example, this study provides greater insight into how optimization can support decision-making on water diversion management under uncertain future environmental conditions. Moreover, it further supports the identification of temporal and spatial scales relevant to the implementation of an adaptive approach for diversion management planning at the basin scale, while also highlighting the importance of incorporating instream ecological requirements into model development.

4.3. Materials and Methods

4.3.1. The Pas River Basin

The Pas River basin (Figure 16) is located in the North of Spain (Cantabrian region) and covers an area of 650 km2 (approx.) with an average elevation of 446 m. The Pas River is characterized by a length of 57 km and a mean slope of 34%. Its network comprises three main rivers (Pas, Pisueña, and Magdalena) that drain into the Cantabrian Sea (Northeast Atlantic). With a mean annual precipitation of 1300 mm, the region’s temperate climate provides significant precipitation throughout the year, generating a mean annual daily flow of 14 m3/s close to the river mouth. The river supplies drinking water to the population of the different municipalities in the region, including the metropolitan area of Santander (> 170,000 inhabitants) and its surroundings. Water abstraction from the Pas River is carried out by daily diversion of river surface water (by cross-channel weirs and pumps) at multiple locations throughout the network to satisfy bid-based municipal water allocations. Moreover, the Pas River is the habitat for iconic species such as the Atlantic salmon or the EU-protected alder-ash riparian forests. It is expected that increasing human water demands and changing environmental conditions, such as reduced forest cover in the catchment, reduced precipitation, and higher temperatures from climate change will lead to growing pressure on the ecological integrity of the Pas River ecosystem (Belmar et al., 2018; Pérez Silos, 2022). The intensification of these drivers can affect the provision of essential Ecosystem Services (ES) in the whole basin, such as those related to regulating and maintaining key ecological processes, conditions, and habitats (i.e. Supporting ES). In this study, a set of 230 target sites (i.e., individual river segments with a maximum length of 500 m, hereafter referred to as RS) were extracted from the cartographic information of the river network data by considering only river segments that were of stream order ≥ 4. Each RS of the set considered in the assessment carries individual hydrological information.

Figure 10 **Case study.** The Pas River basin in the Cantabrian region (Northern Spain).

4.3.2. Problem perception and problem formulation phase for the Pas River Basin

An optimization assessment for water management typically starts with the identification and contextualization of a water management problem by defining objectives, targets, and goals (Horne, Konrad, Webb, et al., 2017), followed by the definition of the optimization model in terms of simulation assumptions and conditions (Derepasko, Guillaume, et al., 2021; A. Horne et al., 2016). These two phases can be described as the problem perception and problem formulation phases (see Derepasko, Guillaume, et al., 2021; Maier et al., 2014) as illustrated in Figure 17. The two-step process is presented for the Pas River basin.

Problem perception: objectives and optimization goals

Contextualization helps to identify important values for river water management. Although a participatory approach can be used to contextualize the management problem (Pahl-Wostl, Mostert, et al., 2008), for simplicity, we have formulated the overall management priorities for the Pas River basin as municipal water diversion planning to sustain ecosystem processes.

As part of the problem perception phase, we considered the improvement or maintenance of ES supporting the biodiversity in the Pas River basin while simultaneously providing sufficient water for the municipalities as the primary management planning objective (Figure 2, top box). With this management objective in mind, we considered the provision of adequate instream hydrological conditions as an assessment target. Such conditions are the basis for setting the optimization goals to meet the ecohydrological requirements for key instream ES indicators (fish, macroinvertebrates, and primary producers; see Section "Environmental Indicators – Definition of relevant ecosystem services for the Pas River").

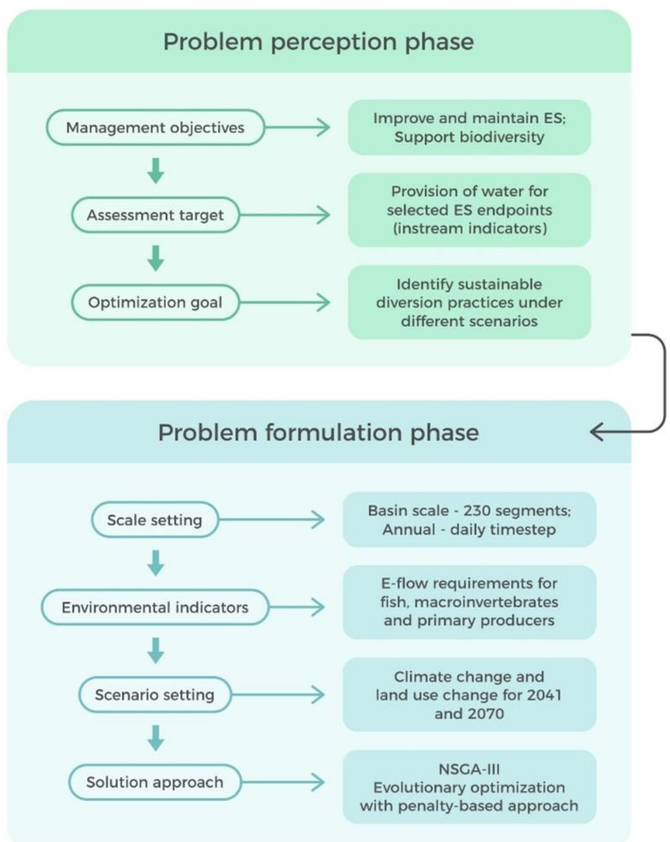


Figure 11 **Summary of the optimization assessment steps implemented in this study throughout the problem perception and formulation phases** (adapted from Derepasko, Guillaume, et al., 2021)

Problem formulation

Based on the optimization goals identified in the problem perception phase, the problem formulation phase (Figure 17, bottom box) envisaged the following methodological steps. Regarding the modeling scale setting, the entire river basin network is considered to be the appropriate scale for both management and modeling. A spatial resolution of 500 m segments was set to allow local scale exploration on a daily time step within the year. The length choice was based on an existing Pas river network data layer. The next step consists of the processing of plausible environmental change scenarios (i.e., reference historical and future conditions of climate and land use) as a testing ground for the considered management planning objectives (i.e., optimization objectives) at two time points (2041 and 2070). In the following, the definition of expert knowledge-based e-flow requirements (including the related time-frame) for key instream biological groups (fish, macroinvertebrates, and primary producers) underlying the Supporting ES indicators is carried out. Finally, an appropriate solution approach (i.e., evolutionary optimization) is chosen for the optimization problem to minimize the violations of the target hydrological metrics while maximizing the total water available for municipal consumption (see section "Solution Approach to the optimization problem").

Scale and scenario setting

Land cover can change the magnitude and variability of instream flow attending to its influence on several runoff processes in the catchment (M. Kumar et al., 2022; Qazi et al., 2017; Sampurno Bruijnzeel, 2005; Zeiger & Hubbart, 2018). Hence, different land cover and climate change scenarios can be used to simulate the resulting river runoff in the basin.

To capture changes in river runoff throughout space and time, we set the spatial scale of the assessment to the stream order ≥4 river network composed of 500 m long RS at the daily time step. The hydrological data used for optimization simulation were provided by the Instituto de Hidráulica Ambiental de la Universidad de Cantabria (IHCantabria) and developed under the (The ALICE Project) for three environmental scenarios in the basin, considering historical (baseline) conditions and two plausible future conditions (Table 10). Figure 18 shows an overview flowchart of the main steps related to the problem formulation phase. The environmental scenarios accounted for land use (LU) and land cover (LC) changes and future climate change projections:

- The LU and LC scenarios were developed using the process-based model framework FORE-SCE Model (Forecasting scenario for land change modeling) (T. L. Sohl et al., 2007; T. Sohl & Sayler, 2008). The FORE-SCE Model simulated current land use and cover by processing elevation, slope, and orientation and modeled fire recurrence. Furthermore, it models the influence of socioeconomic drivers obtained from interviews with local stakeholders and experts in agricultural and urban development policy fields. The input LU and LC maps were derived from historical remote sensing data (Landsat / Sentinel-2 imageries) for the 1990s, 2000s, and 2018 at a spatial resolution of 10 m.
- For climate projections, historical data (from 1950 to 2018) and future data (from 2041 to 2070) on temperature and precipitation were used. See the procedure described in (Fonseca et al., 2022).
- The final accumulated river surface runoff data (i.e., the resulting flow in the river) were produced by applying the distributed hydrological model SPHY (Spatial Processes in Hydrology; (Terink et al., 2015) at a spatial resolution of 100 m and at the daily time step. Historical precipitation and temperature data for the period 1950 to 2018 were retrieved from the E-OBS v20e database (Cornes et al., 2018) and resampled to produce a spatial resolution of ~1 km. (Fonseca et al., 2022) performed a statistical downscaling of precipitation and temperature with Ordinary Least Squares with yearly daily means using latitude, elevation, and Euclidean distance to the coastline as explanatory variables. For future scenarios, climatic datasets from a five-member ensemble of GCM-RCM chain simulations were retrieved for the development of climate change projections for the Pas catchment (Fonseca et al., 2022). Further details of the procedure to develop climatic historical and future series can be found in (Fonseca et al., 2022). Details of the model parameterization are provided in Table A1 in the supplementary materials. As shown in Table A2 in the supplementary materials, the results of the SPHY simulation (which are used by the optimization model) are characterized by a decline in precipitation and an increase in temperature and water demand due to land use changes. This, in turn, leads to a rise in actual evapotranspiration, causing a decrease in average instream flow in the Pas River basin, with a mean flow reduction rate of 25% between the basin outlets in the 1980-2012 and the 2041-2070 periods.

To obtain the hydrological time series for the hydrological year, starting on October 1st and ending on September 30th, with a resolution of 500 m, each RS was linked to the nearest cell value of each scenario dataset (i.e., raster layer of simulated daily averaged accumulated surface runoff for the period 2041-

2070). Two time points were considered for each scenario (i.e., 2041 and 2070) to explore the scenario-related simulation outputs of the water diversion planning objectives defined in Section "*Solution approach to the optimization problem*". The choice of 31 years between the considered time points was intended to capture all possible changes in the basin based on the pre-set conditions to facilitate results comparison. Moreover, we believe this gap can be useful for management purposes. For reference, a hydrological series belonging to the year 2006 was extracted from the historical scenario and used as a present-day baseline. This particular year was chosen because it was the closest representation of a year with normal water conditions. For further insights into these results, we refer to the percent coverage distribution for the different land cover types under each scenario provided in Table A3 in the Supplementary Materials.

Table 10 **Details of the scenarios considered in the optimization assessment for the Pas River basin.**

Timeframe of source data		**Considered period for modeling**	**Scenario name**	**Description**
Historical	1980-2012	• 1/10/2005 - 30/9/2006	*Present day (PR)*	This scenario represents present-day land cover and present-day climate. It is used as a comparison to the historical conditions.
Future	2041-2070	• 1/10/2041 - 30/9/2042 • 1/10/2069 - 30/9/2070	*BAU future (CC_BAU)*	This scenario assumes river discharge is affected by Business as Usual (BAU) future land cover and future climate (RCP 8.5; (Riahi et al., 2011). It considers the evolution of present-day land use and land cover conditions. In particular, forest patches (monoculture planted forest) development is implemented but not prioritized with the presence of shrubs and rushes. In the upper basin, there is a significant rural abandonment with forest recovery from pastureland, whereas the lower basin is characterized by urban area expansion and agricultural intensification.
			Nature-based solutions prioritization (CC_BGIN)	This scenario assumes an investment in nature-based solutions and an RCP 8.5 climate change intensity conditions (Riahi et al., 2011). Concerning the "future conditions" scenario, we have a modification of the rules for land use-land cover evolution (e.g., no fires and forest transitions are favored in places where it can have the highest impact on regulatory ES). This results in a prevalence of hill-side forests (e.g., oak, beech, chestnut, birch species) and riparian forests (e.g., willows, ash, alders).

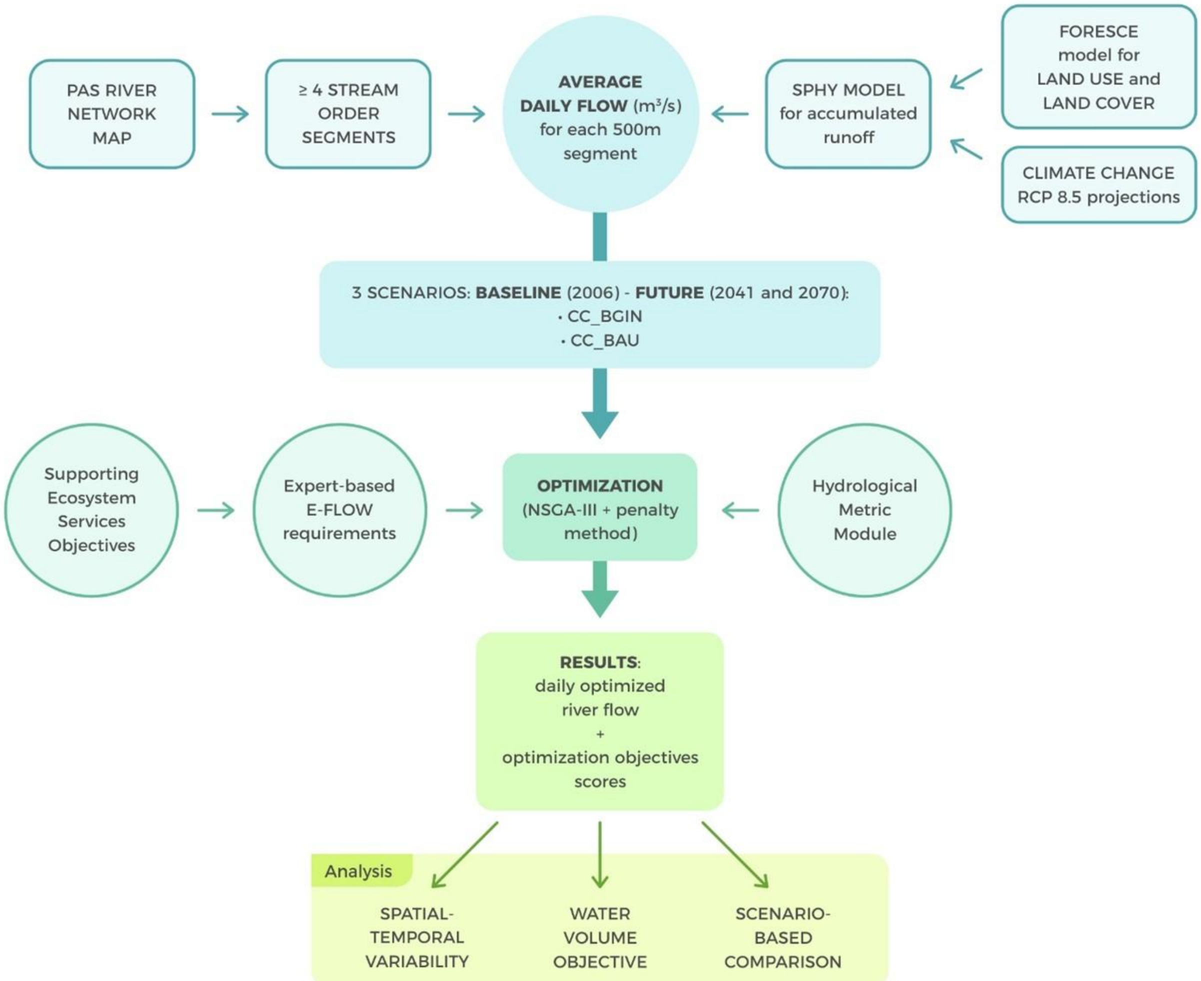


Figure 12 **Flowchart of the steps implemented during the problem formulation phase.**

Environmental indicators - definition of relevant Ecosystem Services for the Pas River

The ecosystem services (ES) concept emphasizes the significance of essential environmental assets and lends itself as an indicator of sustainable management strategies' effectiveness at broader scales (Hauck et al., 2013). River ES supply is heavily reliant on the maintenance of in-stream conditions as the ecological processes and functions are strongly connected to specific attributes of the flow regime (Gilvear et al., 2017; Ibáñez, 2021). As a result, in order to safeguard and preserve ES, hydrological conditions can be elicited to prioritize target ecological processes and functions and species requirements (Alan Yeakley et al., 2016; Ferreira et al., 2022; Gilvear et al., 2017; Jähnig et al., 2022).

In this study, we defined three Supporting ES indicators by explicitly associating them with specific environmental flow (e-flow) requirements for key ecosystem components representing three levels of the river ecosystem food web. The Supporting ES category was chosen because the flow attributes underlying the supporting services can be easily related to the e-flow needed for habitats, life stages, and processes. Moreover, while there is a higher emphasis on Provisioning ES as it provides the most evident benefit to society (Alan Yeakley et al., 2016) Supporting ES can be a valuable indicator for river diversion management as it helps to define minimum standards for sustainable river water diversion.

We assumed that failure to meet the specified e-flow requirements would adversely affect the supply capacity of a specific Supporting ES. This simplification was essential since the optimization simulation we presented cannot quantify the reduction in the supply of Supporting ES and is not meant to explicitly account for synergies and linkages between different categories of ES. E-flows for key ecological components of the river ecosystem (fish, macroinvertebrates, and primary producers) were incorporated into the optimization assessment by considering distinct ecological endpoints as targets. Such ecological endpoints correspond with development stages (e.g., fish spawning) or taxonomic indicators (e.g., highest macroinvertebrate richness) connected to flow events or conditions in a specific time window throughout the hydrological year. We used a set of flow indices based on expert judgment as limiting conditions to diversion to represent hydrological thresholds for the selected ecological endpoints, reflecting Supporting ES supply. In other words, river flow optimized for diversion takes into account the hydrological conditions that must be met to sustain Supporting ES supply in the basin. More specifically, the Supporting ES considered were: Provision of habitat conditions for fish, Life-supporting conditions for macroinvertebrates, and Primary productivity. A description of the considered Supporting ES is shown in Table 11.

The definition of e-flow requirements underlying the Supporting ES indicators was obtained from (Derepasko, Peñas, et al., 2021). However, to reflect more realistic conditions and in the light of novel evidence data the hydrological and temporal thresholds were adjusted for this study. A summary of the e-flow requirements and thresholds used in this study is available in Table A4 in the Supplementary Materials. For a detailed description, please refer to (Derepasko, Peñas, et al., 2021).

Table 11 **Description of the river Supporting ES indicators linked with the e-flow requirements considered in the study**

Supporting ecosystem service	**Indicator description**
Provision of habitat conditions for fish	Hydrological regimes linked with the maintenance of habitat conditions that support main life stages (i.e., migration, spawning, hatching, recruitment), especially during dry periods, and ensuring the occurrence of peak flows (e.g., for migration).
Life-supporting conditions for macroinvertebrates	Flow magnitude and variability conditions. Based on the occurrence of high flow events that promote the highest taxa occurrence probability (itself based on the Intermediate Disturbance Hypothesis; (Osman, 2015b).
Primary productivity	Hydrological conditions of minimum flow during dry periods fostering the maintenance of primary producers (i.e., establishment success and their ability to develop cover).

Solution approach to the optimization problem

Optimization models are computational tools that solve conflicting objectives, such as those related to water diversion management and planning in large river basins. Such conflicts often arise between the demands for river water to support the river ecosystem and for human use on the other side (for additional examples of water management conflicts, see (Derepasko, Guillaume, et al., 2021).

Before defining the technical features of the optimization model, we evaluated different solutions in the sense of a solution concept to better reflect the modeling needs and increase transparency in the model development process (sensu Derepasko, Guillaume, et al., 2021). One solution to the problem follows a top-down approach, limiting the daily water demand (i.e., diversion) based on the annual water demand of all municipalities in the basin. The remaining daily river flow would be tested against the defined e-flow requirements. However, with this approach, it is more likely that ecosystem needs will not be met, and quantifying medium- to long-term needs is complex and adds to existing uncertainty. On the other hand, a bottom-up approach that matches e-flow requirements with available flow increases the chances of maintaining ES and, in a cross-scenario assessment, can identify diversion planning needs for environmental change adaptation. Hence, we decided to follow the latter approach.

Based on the selected Supporting ES and linked hydrological indicators, the optimization problem was characterized by four conflicting objectives (i.e., three for ES and one for the human supply). The human supply objective corresponds to the maximum amount of water that can be diverted from the river to meet human needs (i.e. municipal) as described in Section 1A of the supplementary materials. The optimization model was set to maximize the flow (in m^3/s) that can be diverted for human supply while minimizing the non-compliance of defined e-flow requirements underlying the three Supporting ES. A penalty-based solution approach was implemented to penalize e-flow objective functions when a violation of the specified constraints (i.e., constraints to the water flowing in the river and potentially available for diversion) was detected. In this way, we formulated an unconstrained optimization problem but considered certain conditions that had to be met to obtain solutions with minor violations. In the penalty method, which is integrated into the objective functions, each flow condition that is below the threshold is penalized by the algorithm based on the degree of the violation. Scaling between zero and one (i.e. best and worst result respectively) is applied by normalizing the violation based on the individual constraint features. For a detailed explanation of unconstrained optimization and penalty methods, see (Coello Coello et al., 2002, 2007). The mathematical equations defining the optimization problem are presented in Section B of the supplementary materials.

Evolutionary optimization was used to solve such a non-linear optimization problem, following the approach of (Derepasko, Peñas, et al., 2021). The optimization model was developed using the Pymoo (Multi-objective optimization in Python) framework version 0.4.1. (Blank & Deb, 2020b) for the NSGA-III (Non-Dominated Sorting Genetic Algorithm III). The genetic algorithms (GA) at the base of the Pymoo optimization framework are very versatile, as they allow the simultaneous optimization of multiple objectives by imitating the process of natural selection of eliciting chromosomes throughout the search process (Cavazzuti, 2013). The NSGA-III (Deb & Jain, 2014; Jain & Deb, 2014) provides a good chance of rapidly approximating a globally optimal solution. A hydrological metric module was run with the Pymoo optimization framework to calculate the hydrological indicators used for the e-flow requirements at each generation. An initial random population of “optimal” discharge volumes (in m3/s) is generated by the algorithm. The fitness of the residual discharge in the river (difference between the scenario-based reference discharge in the river and the “optimal” discharge volume) is evaluated at each generation based on the degree of penalty violations for each optimization objective.

In the present study, the optimization model framework was run once for each independent RS within the considered time point and scenarios (i.e., five total model runs per scenario setup), generating unique results for each RS. The output of each model run was 230 optimal discharge volumes (i.e. one for each RS) for each scenario. The choice to run the optimization algorithm only once for each RS and scenario was based on the algorithm performance reported in the initial study by (Derepasko, Peñas, et al., 2021). The study by (Derepasko, Peñas, et al., 2021) showed that a model set up envisaging 1000 generations (for 100 individuals) was appropriate for the convergence of the solution front to the ideal (i.e., its approximation). This was confirmed by a Running Metric Indicator (Blank & Deb, 2020a) real-time measuring the objectives space from one generation to another that found similar patterns in the results from multiple simulations. The Running Metric is useful when termination criteria are not stated. An example of the convergence is given in Figure 1B in Section B of the Supplementary Materials. The final population of optimization scores was produced by implementing a preference-neutral approach by averaging the optimization objectives scores of the optimal population.

4.4. Results

4.4.1. Performance of the optimization objectives

As a first step in the analysis of the results, we evaluated the performance of the optimization objectives under the different scenarios, i.e., the total water volume available for consumption (i.e., municipal supply) while maintaining the prescribed diversion limits. The simulation results show that the optimization objective (i.e., the total volume of river water in Hm3/y) can satisfy the water demand of the municipalities in the Pas River basin of the projected water demand for the year 2040 (i.e., around 7 Hm3/y) (Gobierno de Cantabria, 2020). However, the water volumes differ significantly between the scenarios considered. While the baseline simulations (for the year 2006) predict an average of 91.1 Hm^3/y available for diversion, the future scenarios (for the year 2041) predict 86.9 and 86.7 Hm^3/y for the CC_BGIN and CC_BAU respectively. For the same scenarios under future 2070 conditions, the model simulated 67.4 and 70.4 Hm^3/y available for diversion. These results can be linked to the ability of the SPHY model to generate projected hydrological data to capture interactions between flow and land cover (e.g., the extent of forest cover vs. maturity).

On the other hand, the optimization results for the selected ES indicators along the river network (see Figures C1-3 in Section C of the supplementary materials, Figure 19 shows results for Habitat condition provision for fish life-stages ES) show the highest scores (i.e., least optimal results) for the provision of suitable habitat conditions for the different life stages of fish. This is observed in particular for the downstream river segments of the basin. At the same time, the highest heterogeneity of optimization scores is achieved in the upstream reaches in both the future BGIN_CC and BAU_CC scenarios. Optimization scores are absolute values that measure the conditions for achieving ES objectives. Values closest to zero represent the optimal conditions for ES for a given model simulation. While higher scores (> 3.0) in the 2006 baseline scenario (PR) indicate existing hydrological pressure on the specific indicator, the reduction (scores between 0.9-1.6) of the optimization scores in the future scenarios increased the capacity of the river system to provide habitat conditions for fish. Conversely, a reverse pattern emerged for the ES indicator primary productivity, where the results show the highest optimization scores in the upstream reaches. Interestingly, the macroinvertebrate objective was zero at each RS and scenario, indicating that the baseline and projected river flow could meet the defined instream conditions.

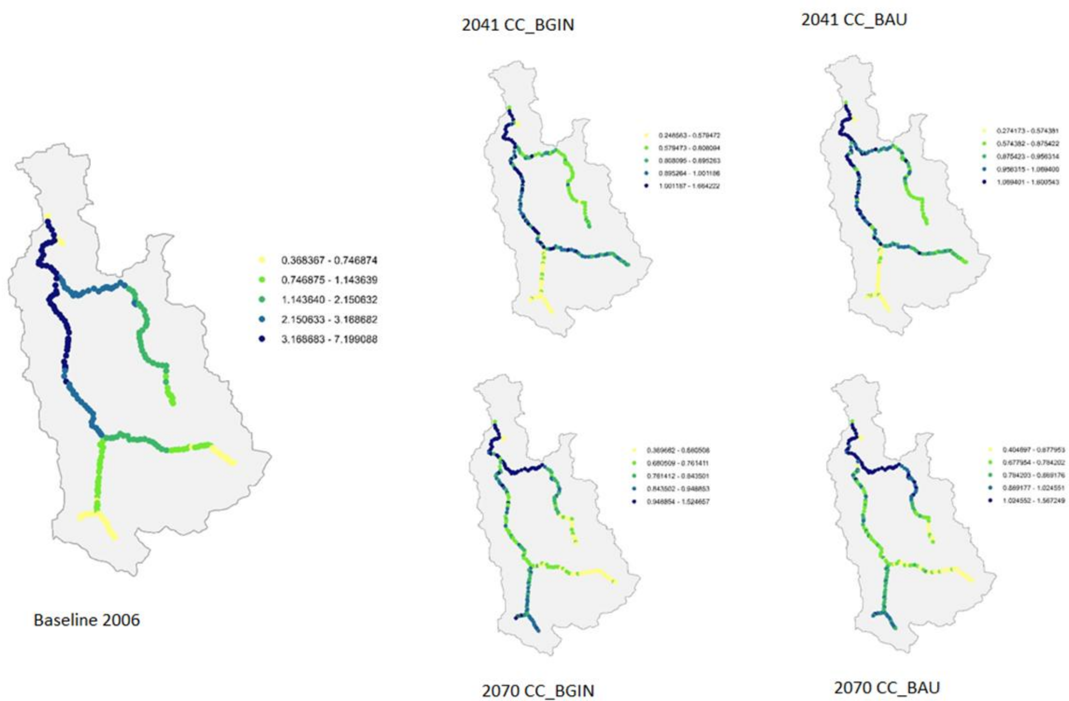


Figure 19 **Maps showing the spatial distribution of the optimization objective scores for the Habitat condition provision for fish life-stages ES under each considered scenario.** Values closest to zero indicate the best achievement of the objective at a specific RS. The classification scheme follows the quantile chromatic classification approach: Blue shades = highest scores (worst results), yellow shades = lowest scores (best results). Note: each map presents min-max values that differ from each other as the figure aims to highlight scenario-specific spatial variation of the scores.

However, this result may also be due to the type of hydrological indicator considered for the specific optimization objective. Furthermore, small inlets close to the downstream segments of the main river network are characterized by reduced optimized discharge with respect to the remaining river network due to their reduced discharge and variability.

4.4.2. Spatial and temporal distribution of water available for diversion in the Pas River basin

The second objective of the assessment was to evaluate the spatiotemporal distribution of water available for diversion in the Pas River basin after optimization. In the first step, we investigated the spatial distribution of the optimized daily river discharge available for diversion. The daily values of the river flow optimized for diversion in the Pas River basin can be accessed as an interactive map for each scenario at the following link: https://doi.org/10.6084/m9.figshare.19636449.v4 (Derepasko et al., 2022). The monthly averaged static maps of optimized instream flow for the baseline year (2006), and the 2041-2070 CC_BAU and CC_BGIN scenarios are available in Section C (Figures C4-8) of the supplementary materials. Upstream river segments showed higher variation in the water volumes optimized for diversion than downstream segments. Upon comparison of the different scenarios, it is evident that the observed pattern remains consistent across all environmental conditions considered in the simulation. This consistency could be attributed to the chosen hydrological indicator (i.e., cumulative runoff for each segment of the river) and the anticipated increase in flow magnitude as the river network approaches its outlets. Lastly, we analysed the simulation results by looking at the seasonal river discharge averages to explore which time scales are particularly relevant for management and policy. Figure 20 depicts these findings. The results show a decrease in the average optimized discharge for the fall season for both scenarios in 2070. However, a slightly higher average optimized discharge is observed for the spring and summer seasons. In all future scenarios (2041-2070), there is a decrease in the average flow available for diversion during winter. Although there were minor differences in the overall trends between the BGIN_CC and BAU_CC scenarios, the variations were not significant.

QR code for the https://doi.org/10.6084/m9.figshare.19636449.v4

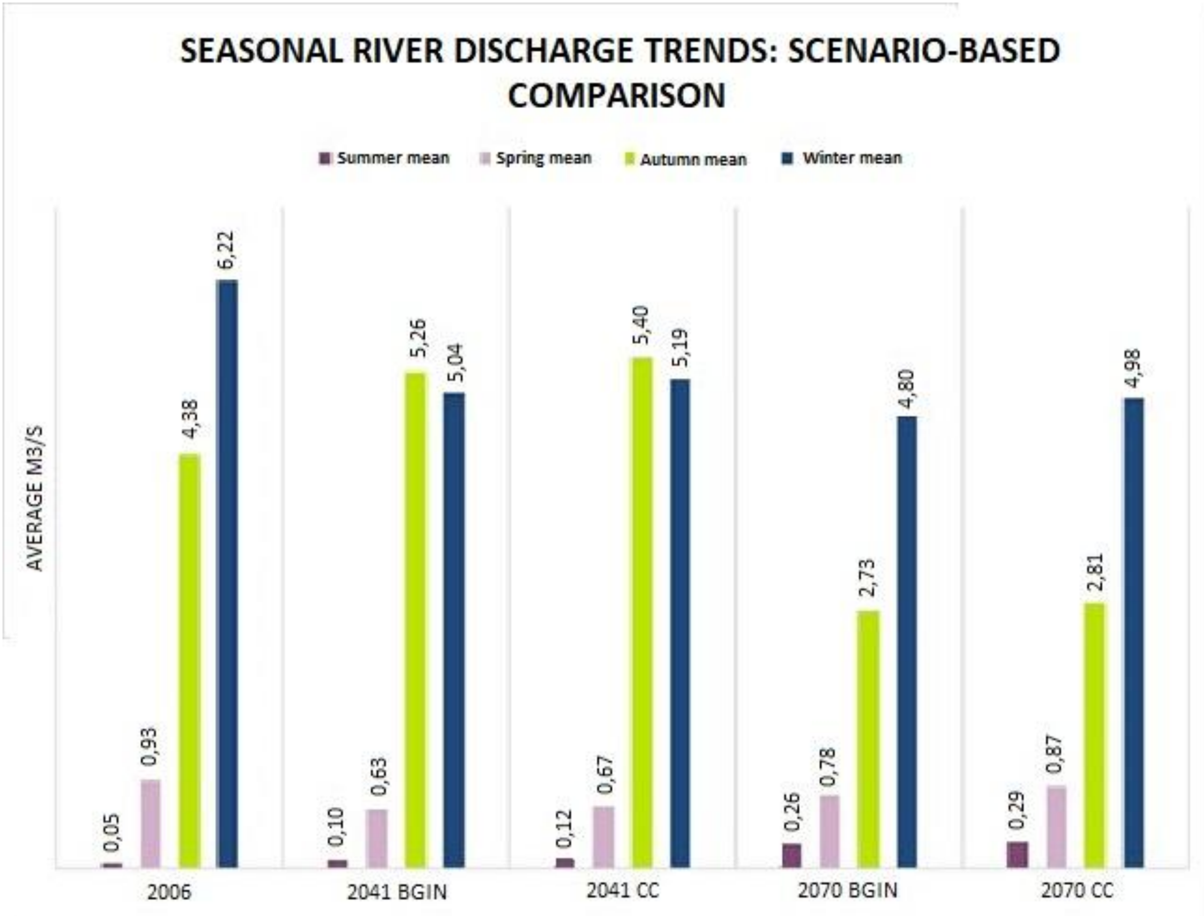


Figure 20 **Seasonal river discharge trands.** The histogram shows the scenario-based comparison of the optimised seasonal river discharge values expressed as average seasonal flow (in m³/s) for the entire river network. CC=CC_BAU (business-as-usual land cover under RCP 8.5 climate forcing scenario; BGIN=CC_BGIN (prevalence of nature-based solutions under RCP 8.5 climate forcing scenario.

4.4.3. Comparison of results within the different scenarios

To understand the rate of variability in average discharge values throughout the year, we processed the results as a frequency distribution of average discharge values under each scenario. An illustration of this for the baseline scenario can be found in Figure 21. Additional findings are available in Figures C9-12 in Section C of the supplementary materials). The results show that the most significant variability in optimized average discharge values throughout the basin is likely to occur from December to March, whereas the period spanning May to October proved to be the most stable.

Due to the amount of data generated, four RS were selected to illustrate in detail the results of different locations along the river network and to analyze the results at different locations in the river network (see

Figure C9 in Section C of the supplementary materials). To examine the interannual trends, we plotted the natural flow against the flow resulting from the optimization simulation and available for abstraction for the four representative RS (Figure 22); see “A-B-C-D” in Figure 23 as an example for the BGIN_CC scenario of the year 2041 (other results are available in Figures C14-17 of the supplementary materials). The comparison of the natural flow and the optimized flow for diversion between scenarios shows that for most of the year, a sufficient portion of the river flow is available for diversion (i.e., the optimized flow mainly follows the natural flow regime), demonstrating a reduced trade-off between objectives (i.e., municipal supply and ecosystem services). However, during the driest periods of the year, a larger proportion of the flow is needed to maintain and meet ecological thresholds.

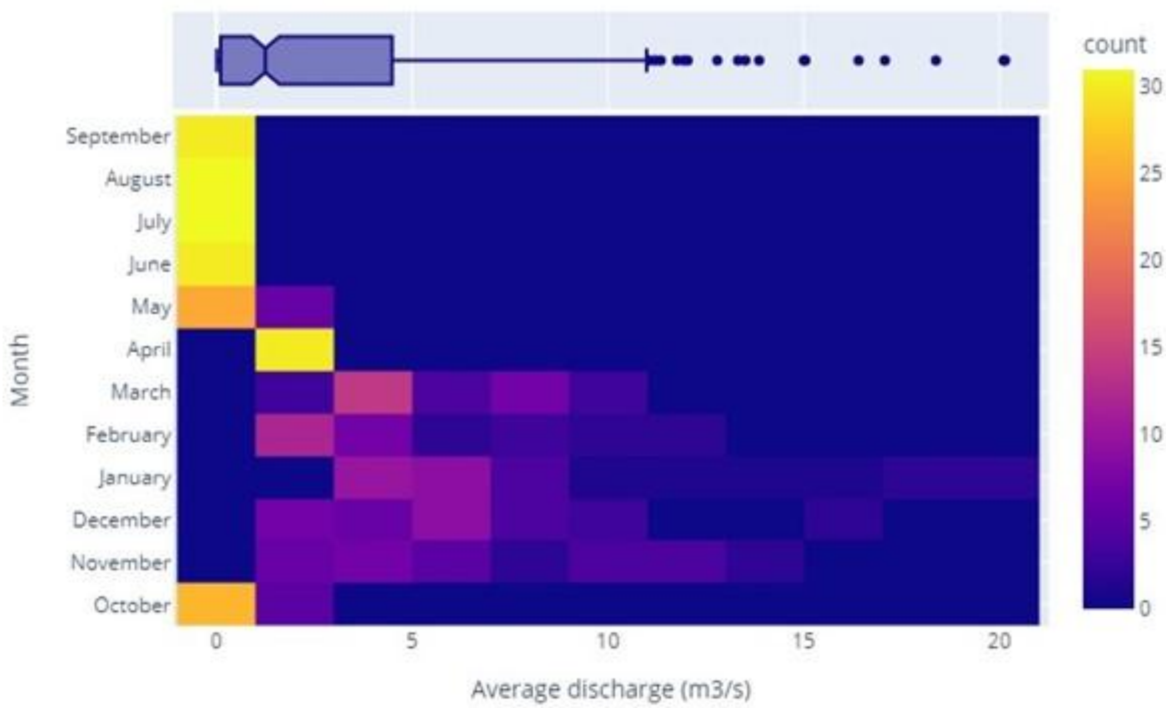


Figure 21 Heatmap showing the average optimized discharge (in m³/s) value (on the x-axis) for each month (on the y-axis) for the baseline scenario in 2006 for the entire river network. On the right-hand side of the box is a color-based classification of the frequency of occurrence of each range of values; at the top of the box, a boxplot shows the yearly quartiles, extremes, and outliers. The figure highlights periods (months) of greater or lower variability suggesting critical months of the year (providing hence a temporal implication for diversion) for diversion planning, which in our view would require additional exploration

Notably, in the 2041 scenarios, the model identified a lower optimal discharge during the dry months despite a prominent natural flow, indicating a greater trade-off based on ecological needs and defined requirements.

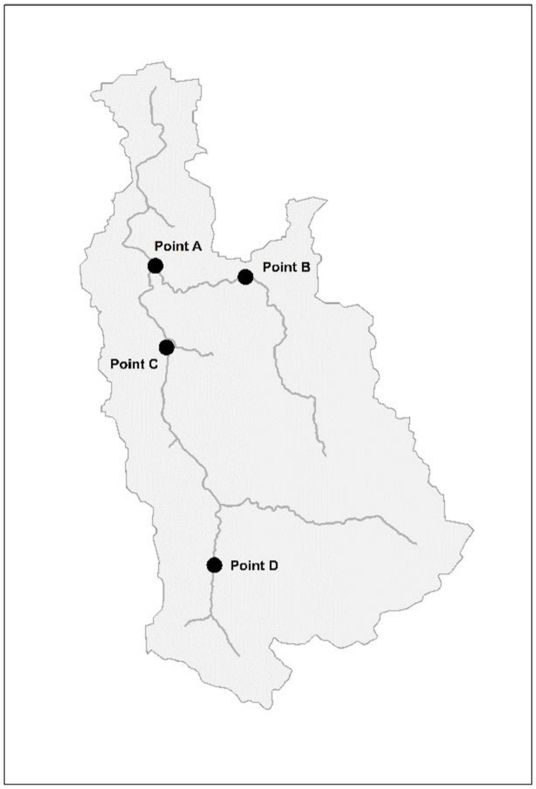


Figure 13 **Four representative RS in the Pas River basin.**

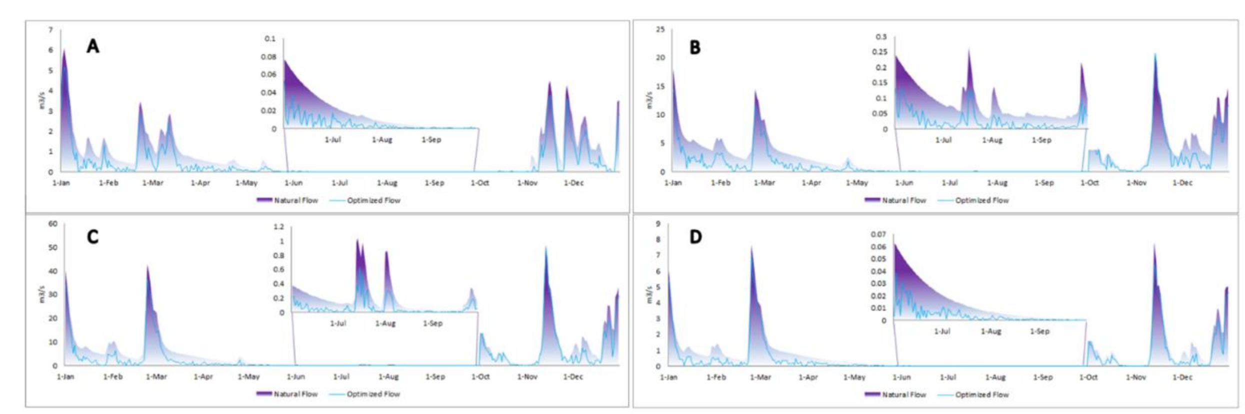


Figure 14 **Flow series showing the daily profile of the discharge (in m³/s) optimized for diversion (light blue thin line) plotted against the river's natural discharge (purple background shape)**. Example of four selected river sections (RS locations "A," "B," "C", "D") analyzed under the 2041 BGIN_CC scenario. More pronounced differences between the lines indicate the highest trade-off periods between the natural discharge and water for municipal use.

4.5. Discussion

4.5.1. Spatial and temporal scale considerations of water available for diversion

Knowledge of the future spatial and temporal variability of water available for consumptive needs (e.g., drinking water) provides an advantage for water diversion management that aims at reducing uncertainty in management outcomes. Although it is not possible to provide absolute results (because we cannot reduce all potential sources of uncertainty; (Kirchner et al., 2021; Maier et al., 2016), evaluating objectives under a range of scenarios can help identify appropriate management strategies in the present to achieve long-term diversion goals. From a spatial perspective, typically most basin management strategies focus on the entire network or significant parts to achieve specific downstream abstraction objectives (Gawne et al., 2018). Our results showed that while river water optimized for diversion can meet annual municipal water supply under all scenarios, the average daily and monthly optimized flow can vary significantly at different locations in the river network, which poses a challenge for maintaining adequate conditions for ES throughout the year and providing supply during dry periods. To address this, diversion management can define site-specific water supply targets and support the ecosystems' hydrological needs. Furthermore, river and land management planning could consider relocating abstraction-dependent facilities downstream where discharge is more stable. From the temporal perspective, our study has found that downstream river segments maintain a more stable optimized discharge throughout the year compared to upstream river segments, which experience greater variability. This pattern was observed across all scenarios and can be attributed to the higher sensitivity of upstream reaches to climate events.

However, more research is needed to evaluate the influence of land cover and instream flow in these areas. Although these results are related to our case study, they underline the importance of analyzing temporal hydrological patterns across the entire river network.

Our study suggests that the main challenges for basin management under the scenarios considered are related to the pronounced seasonal differences in optimized discharge at each river segment, leading to spatial heterogeneity across the network. Incorporating these spatial and temporal aspects into management planning, for example by distinguishing between river segments that exhibit the greatest variation in streamflow over the course of the year, would help reduce the risk of major trade-offs in river water allocation in future diversion programs and promote the implementation of adaptive management.

4.5.2. Supporting ecosystem services objectives across scenarios

Our study assessed the future sustainability of diversion decisions by examining optimization scores change between time points in the short and medium term (i.e., 2041 and 2070) and scenarios at each river segment. In regulated basins, maintaining conditions for fish is typically a critical water management objective because of their intrinsic value and connection to other ES supply (e.g. fisheries, recreational) (Watz et al., 2022). Fish species require a range of specific hydrological conditions for each life stage. The ES objective ‘provision habitat conditions for fish life stages’ showed high optimization scores (i.e., least optimal result) in the downstream reaches in the baseline scenario. These scores decreased in both CC_BGIN and CC_BAU scenarios, with slight additional improvement (i.e. slightly lower scores) for the year 2070. While downstream reaches are usually characterized by more stable discharge, this result could be related to the simulation conditions. However, it is crucial to take into account the influence of severe occurrences on hydrological behavior. Such events might have disturbed the timely flows of freshwater and peak flows, resulting in affecting the model's fish requirements. Conversely, the ES of ‘primary productivity’ required stable low-flow minimum conditions throughout determined periods in the year, resulting in a higher score for upstream reaches in both scenarios and time points. This indicates that water diversion planning trade-offs involve the priority of supplying low flows upstream of the river network while ensuring that peak flows downstream are maintained. Other studies also found that upstream water abstraction impairs downstream ecological functions and can expose the basin to water scarcity (Alvarez-Garreton et al., 2023). On the one hand, our results confirm that even enough natural discharge downstream of the river is not sufficient to ensure the achievement of optimal scores for all ES objectives considered. However, this could also be related to the differences in the formulation of the equations at

the base of the optimization objectives (e.g. the indicators chosen). A possible solution could be distinguishing areas where ES are generated and consumed, as suggested by the study of (Alan Yeakley et al., 2016). This can likely reduce this bias by regarding only locations where Supporting ES are generated.
The Supporting ES objectives scores showed significant variability in their specific supply capacity (Provision of habitat conditions for fish ES, Life-supporting conditions for macroinvertebrates ES, Primary Productivity ES) throughout the network while the comparison of the scenarios (CC_BAU and CC_BGIN) didn't show any noticeable difference. Instead, trade-offs were found to be inherent in the spatial and temporal dimensions of diversion planning. Thus, failure to recognize the spatial variability of discharge conditions for each RS under consideration may result in overlooking hotspots of reduced supply that must be investigated to achieve long-term management objectives. While the results of implementing such goals need to be monitored to verify their durability in the real world, the results of our study showed that, overall, the considered e-flow requirements (i.e., hydrological indices associated with ecological processes) can provide a good compromise for diversion water management needs to ensure sufficient river water for key ecosystem endpoints and municipal needs.

4.5.3. Optimization set-up and scenarios for water diversion management at different scales

Defining a set of plausible conditions under which the model will "operate" or be tested is the second step after defining the model. In optimization, this usually corresponds to establishing rules and objectives and then running the model for specific input conditions (e.g., hydrological, climatic, and LU and LC patterns) (Derepasko, Guillaume, et al., 2021; A. Horne et al., 2016). The input conditions can be calibrated based on projected changes in environmental drivers (i.e., scenarios) that could affect the system. Critical drivers of change in river basins (and the water they provide) include, in particular, land use and climate change (Gedefaw et al., 2023; Iqbal et al., 2022; Kaushal et al., 2017), which introduce a large degree of uncertainty in the results obtained. While uncertainty can be treated in different ways in optimization modeling, (McIntosh et al., 2011) points out that "decision-makers are not particularly interested in uncertainty per se […]. Rather, they are interested in knowing whether particular decision strategies are robust across a range of possibilities". This range of possibilities can be more or less roughly represented by scenarios, which can be used to identify management plans and strategies independent of future conditions (Maier et al., 2016).
Based on our explorative research and acknowledging the results from (Derepasko, Peñas, et al., 2021), optimizing environmental change scenarios (i.e., input hydrological conditions, in the case of optimization

applied for diversion) at large scales such as river basins and sub-basins can lead to more effective identification of patterns of spatial-temporal changes in water availability for diversion to prioritize hotspots for shortages. On the other hand, once hotspots have been identified, river segment-specific hydrological features can be tested by modifying optimization constraints (i.e., limiting conditions), for example, by relating hydrological patterns to the response of adjacent habitats, species requirements, and landscape features (e.g. mountains slopes). However, both assessment scales would benefit from good-quality input data and assumptions about system processes (i.e., knowledge of how the system behaves). While the former can be controlled to some extent through careful selection and pre-processing, the latter will always be affected by some degree of uncertainty (i.e., aleatory uncertainty as opposed to epistemic uncertainty; (Maier et al., 2016; Maier et al., 2014) which cannot be eliminated. Another solution to reduce uncertainty is to run the model multiple times. However, this would increase significantly the computational effort and long post-processing times, especially for large river basins. We acknowledge that simplified assumptions about future climate and environmental system states and a few model runs have been made in this study. In addition, the inclusion of an optimization module to take into account the cumulative impact of diverting river water from upstream river segments on the downstream discharge would allow an improved assessment of river flow available for diversion. Therefore, while the exploratory assessment has some limitations that can be addressed in future applications, our modeling application can still provide a simple means for examining the implications of water diversion management decisions by incorporating segment-level information. It's worth noting that the results do not offer an exact representation of the optimized daily flow behavior for each scenario but rather should be used to derive the uncertainty space for implementing future water availability for diversion. To make informed decisions for adaptation of management programs to future conditions (i.e., through informed decisions), it's vital to have a broader view of detailed river flow information such as river segment data at basin scales. Assessing water diversion at small scales provides limited information to managers and reduces their ability to take effective action when changes occur (Capon et al., 2018).

4.5.4. Considerations on optimization indicators for ecological endpoints

In order to effectively manage the impact of river water diversion on instream ecosystems, it is crucial to identify the hydrological conditions that are necessary to support ecological endpoints. The literature provides many examples of hydrological conditions linked to specific ecosystem components (especially biological groups or species) through e-flows (the magnitude, timing, and rate of change), which can be linked to indicators for supporting ES. Regardless of which concept better fits the management needs of the particular case study, to define ecological instream flow requirements for optimization modeling, we recommend taking the following considerations based on our study: (1) Focusing solely keystone species or relevant ecosystem components in the basin is convenient for optimization as it can capture the most critical hydrological components, but it may miss other important hydrological processes. In this case, the choice is either to justify the selection a limited number of ecosystem components or to expand the range of hydrological processes considered in the optimization model, which would require more modeling efforts. (2) Our study results show that optimization scores for supporting ES objectives are unevenly distributed across the basin and scenarios. This suggests that while the scenarios help test the appropriateness of overall management objectives in light of future changes, more insight can be gained by targeting locally tailored ecological objectives. For example, prioritizing some ecosystem components and their hydrological requirements downstream of the river network while focusing on others upstream; (3) Consider the possibility of ecological processes adaptation. More specifically, if the time horizon considers long-term management objectives, it should be recognized that some species adaptation may have occurred by the end of the planned management period while management outcomes are manifested. Failure to account for potential ecosystem adaptations when applying optimization models can skew the assessments and render results useless. Although this may be one of the most challenging tasks for modern water management, many recommendations have already been made in the current literature to account for these changes (Judd et al., 2023). However, more precise information is needed this can be achieved with optimization.

4.6. Recommendations

Based on the results of the exploratory optimization assessment conducted in this study, a series of recommendations were formulated for both water managers and water management analysts/modelers. These recommendations aim to facilitate basin-scale diversion management planning and enable the adoption of an adaptive management approach (see Table 12).

Table 12 **Summary of recommendations to support water managers and optimization modelers in addressing water management problems to increase the potential for incorporating adaptive management approaches.**

User	Issue	Description
Policy and Decision-makers in the frame of water management	Spatial domain	1. Considering river segment-specific hydrological conditions when developing a diversion management plan can help identify areas of more stable discharge conditions for consumptive use.
	Temporal domain	2. Management planning should account for changes in diversion conditions throughout the year by retailoring objectives to seasonal scales.
	Future environmental conditions	3. When planning diversion management, seasonal shifts due to climate and LULC change must be predicted, incorporated, and aligned with future management objectives.
	Ecosystem services	4. Management planning should consider appropriate ES supply indicators and conditions based on the location of the river segment and the conservation objectives.
Mixed	Forest indicators	5. The effects of forest cover prioritization on available river water for diversion would be more evident if forest maturity rather than forest extent is prioritized.
Optimization modelers for water management/ water	Importance of input data quality for optimization assessments	6. Incorporate predictions of ecological adaptation to environmental changes for specific water management horizon.

management analysts	Selection of the most appropriate scale	7. Basin-scale modeling supports management scenario testing, while reach-scale modeling is more appropriate for constraint testing.
	Output type	8. As large scales require extensive input data, setting clear objectives can help to process the volume of output data and clear communication of results.
	ES indicators	9. Prioritize the hydrological requirements of some species downstream of the river network while focusing on others upstream, for example, by applying weights.

4.7. Conclusions

This study considered the Pas River basin as a test site to examine the spatial and temporal implications of river water diversions. The objective of the optimization assessment was to identify future challenges for diversion planning, taking into account the hydrological requirements for key instream Supporting ecosystem services and the annual municipal water demand. Two future environmental change (land use, climate) scenarios were considered. While the daily river water available for diversion was found to meet municipal needs under the considered scenarios, the study results showed that seasonal shifts and spatial heterogeneity in diversion volumes and the optimal provision of ecosystem services represent the most significant challenges for medium- to long-term diversion management. Based on our findings, we provide considerations and recommendations for organizing river water diversion management efforts at the basin scale to achieve an adaptive approach. Diversion planning should consider the seasonal time frame for setting diversion targets and consider site-specific ecological goals that maintain the provision of supporting ecosystem services. In addition, running multiple simulations can help reduce the uncertainties associated with the data in subsequent practical applications.

While the assessment presented in this study can assist in pinpointing viable diversion locations and strategizing withdrawal timing, forthcoming investigative analyses using optimization should incorporate the effects of severe climate change events and insights from enhanced land cover-hydrology modeling.

This entails taking into account the holistic influence of land cover in a given region on river discharge at a designated site and the maturity of local forests. Moreover, conducting several simulations can help mitigate any uncertainties related to data in subsequent practical applications.

Supplementary Materials:

The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/w15183289/s1. Section A, Table A1: SPHY model (see Section 2.2.2.1) input type and their values for the generation of the surface runoff for the river network in the considered case study area; Table A2: Variation of the environmental parameters for the present (1980-2012) and future (2041-2070) periods considered in the study; Table A3: Percentage cover for each class and each scenario considered in the optimization simulation; Table A4: Summary of the e-flow requirements (EFR) considered in the study. The EFR defines the hydrological conditions to be conserved in the river during the daily diversion operations throughout the year. The table shows the duration, the hydrological metric used, and the month of the year relevant for each EFR. Legend: %MMF = percentage value of mean monthly flow; Qm7 = 7 times the median annual flow; Q75 = the flow value that is exceeded 25% of the time; %MYF = percentage value of the mean yearly flow; Section B, Figure B1: The Running Metric Indicator (Blank & Deb, 2020) for a test RS simulation. The Δf indicator measures the convergence of the objective space at each generation. Section C, *Figure C1*: Maps showing the spatial distribution of the optimization objective scores for the Habitat condition provision for fish life-stages ES under each considered scenario; *Figure C2*: Maps showing the spatial distribution of the optimization objective scores for the life-supporting conditions for Macroinvertebrate taxa richness ES under each considered scenario; *Figure C3*: Maps showing the spatial distribution of the optimization objective scores for the Primary productivity ES under each considered scenario; *Figure C4*: Monthly averaged optimized instream flow for the PR scenario (2006); *Figure C5*: Monthly averaged optimized instream flow for the CC_BAU 2041 scenario; *Figure C6*: Monthly averaged optimized instream flow for the CC_BGIN 2041 scenario; *Figure C7*: Monthly averaged optimized instream flow for the CC_BGIN 2070 scenario; *Figure C8*: Monthly averaged optimized instream flow for the CC_BAU 2070 scenario; *Figure C9*: Heatmap showing the average optimized discharge (in m3/s) value (on the x-axis) for each month (on the y-axis) for the 2041 BGIN_CC scenario; *Figure C10*: Heatmap showing the average optimized discharge (in m3/s) value (on the x-axis) for each month (on the y-axis) for the 2041 BAU_CC scenario; *Figure C11*: Heatmap showing the average optimized discharge (in m3/s) value (on the x-axis) for each month (on the y-axis) for the 2070 BGIN_CC scenario; *Figure C12*: Heatmap showing the average optimized discharge (in m3/s) value (on the x-axis) for each month (on the y-axis) for the 2070 BAU_CC scenario; *Figure C13*: Location of the representative points in the basin elicited for results presentation and discussion; *Figure C14-C15*: Flow series showing the daily profile of the discharge (in m3/s) optimized for diversion (light blue thin line) plotted with respect to the river natural discharge (purple background shape) for the each of the four RS locations analyzed under the Baseline 2006 (PR) scenario (top) and 2041 BAU_CC scenario (bottom); *Figure C16-C17*: Flow series showing the daily profile of the discharge (in m3/s) optimized for diversion (light blue thin line) plotted with respect to the river natural discharge (purple background shape) for the each of the four RS locations analyzed under the 2070 BGIN_CC (top) and 2070 BAU_CC scenario (bottom).

5. Synthesis and Discussion

This thesis addresses key challenges in water resource management research by exploring topics such as the connection between modeling and management scales, the importance of integrating environmental flows (e-flows) into management practices, and the necessity for tools to support the implementation of adaptive management. In the context of sustainable water resource allocation, optimization modeling was evaluated as a convenient tool to address these challenges by supporting the decision-making process in balancing competing ecological and human water needs. Nevertheless, several obstacles arise when developing models for water resource management problems, particularly regarding trade-off decisions related to scale and the representation of ecological requirements at different scales. Further challenges are the development of an effective modeling structure to support the implementation of adaptive management and the inclusion of future scenarios. The presented research investigated how optimization models can bridge these gaps by providing the necessary flexibility to incorporate relevant factors such as ecological requirements and future environmental changes.

This chapter synthesizes the main research findings by addressing the research questions and highlighting how the thesis has advanced knowledge in this research area regarding the use of optimization models to support water management decisions. It also reflects on the implications of the findings for the broader issues addressed and the limitations of the research conducted. Finally, the chapter provides recommendations for future applications of optimization approaches that build on the findings of the previous chapters and suggests possible directions for further research.

5.1 Summary of key findings

One of the central research topics explored in this thesis is the interplay between modeling decisions and the assessment scale, explicitly examining how these choices shape spatial and temporal scales in reconciling environmental flows with human water needs. Water management systems are inherently hierarchical, with water flowing through different regions, infrastructures (like dams and reservoirs), and ecosystems that operate on different spatial and temporal scales (Gurnell et al., 2016). Water allocation, river flow management, and infrastructure operation decisions aim to balance objectives like maximizing human use or sustaining ecosystem flows. These decisions span scales—from small river sections to entire river basins, daily operations to long-term planning—each requiring tailored data and modeling. Accurate representation of the management context and scales is critical to the success of management decisions and their outcomes. I have found that an exact match between modeling scales and decision-making scales is often not achievable, leading to necessary compromises.

In Chapter 2, I emphasize the importance of adapting the model's scale to the management problem's objectives. I reviewed case studies of multi-objective optimization models in water management to address the first research question on how modeling choices influence spatial and temporal scales. The analysis examined how management scales were represented and the methods employed to tackle water allocation challenges across diverse contexts, ranging from basin-wide strategies to specific river reaches or reservoir operations. My findings highlight that effective management requires tailoring optimization strategies to the unique characteristics of each river system and its management context, considering factors like planning horizons and approaches to defining e-flows. While some generalization is possible, modelers must prioritize relevant, scale-appropriate information to minimize inaccuracies.

To address the challenge of integrating decision-making scales, data types, and optimization, I argue that recognizing the impact of modeling decisions on spatial and temporal scales is key to understanding trade-offs between the management scale and the simulated scale. This understanding can ultimately improve management outcomes at the desired scale. In this context, Chapter 2 presents a framework I developed to help users navigate these trade-offs and guide the selection of appropriate scales and associated data at the interface of modeling and management. The framework divides the optimization process into two phases: problem perception and problem formulation.

The problem perception phase focuses on understanding the objectives, limitations, and management options of the water management system. Here, I emphasize the importance of collecting detailed system information, such as identifying goals (e.g., water supply for human use or ecological health), constraints, and options for managing water flows. In the problem formulation phase, this understanding is translated into a formal optimization model, requiring the development of mathematical representations of the management problem. While both phases offer flexibility in modeling options, data selection, and reference conditions like e-flow definitions, these choices often fail to fully align with the reference context.

Because the optimization process inherently involves compromises, I advocate for greater transparency in outlining how these trade-offs are made when transitioning from problem perception to problem formulation. This includes explicitly addressing how data and modeling limitations influence the scale of the analysis and acknowledging their potential impacts on management decisions. By making these trade-offs clear, I believe the optimization process can become more robust, providing reliable insights and ensuring models are better suited to addressing ecological and societal needs.

On the whole, Chapter 2 addresses a critical gap in water management literature by offering practical guidance for researchers and practitioners – it provides a simple yet structured approach to understanding and integrating scale in multi-objective optimization models, helping clarify the critical role of spatial and temporal scale in the water management context. This ensures that optimization models are better aligned with the realities of complex water systems. Ultimately, I aim for the proposed framework to be valuable for water managers, offering a tool for reasoning about the appropriate scales and relevant data when developing a water management plan. It is also intended for modelers and provides a comprehensive structure for developing multi-objective optimization models that incorporate e-flows and help achieve a satisfactory representation of the target spatial and temporal management contexts.

Building on the framework presented in Chapter 2, which highlights the importance of scale in multi-objective optimization models for water management, I have shifted the focus in Chapter 3 to a more technical exploration of optimization model development. Here, I address how to practically integrate e-flows into these models, moving from a broader conceptual understanding to a hands-on approach. I aimed to show how optimization can support the decision-making process while minimizing the need for excessive information processing in both the upstream and downstream stages of the simulation.

The literature offers various approaches for defining ecological water requirements, often relying on software or modeling techniques. I found that optimization provides flexibility, enabling decision-makers to select the level of complexity for incorporating ecological information. In this chapter, I introduce an optimization-based method to balance competing objectives by adjusting water diversion practices to meet ecosystem needs. Using the Pas River in northern Spain as a case study, I incorporated ecological flow requirements for fish, aquatic macroinvertebrates, and primary producers, informed by expert judgment from a workshop with hydrology and freshwater biology specialists. I translated these requirements into thresholds for hydrological conditions, such as flow magnitude and timing, to support key ecological processes like migration and spawning. By applying penalties for unmet flow thresholds, I achieved optimized flows that better reflect natural variability. Simulation results revealed significant daily variability in water availability for diversion, leading me to conclude that seasonal adjustments could be more appropriate for diversion planning than relying solely on annual water supply targets. However, the deviations I observed in the optimized hydrograph, particularly under dry conditions, showed that also natural flow variability imposes baseline stress on ecosystems. This highlights the importance of incorporating flexibility into water management strategies to account for natural fluctuations and address extreme climate conditions.

I believe both modelers and managers can benefit from the demonstrated example of eco-hydrological information processing, gaining insights on translating expert knowledge on ecological flow requirements into indicators to be easily integrated into optimization models. This addresses the research question of how optimization approaches can mediate e-flows in water diversion management and support adaptive management. Through this modeling simulation, I gained a deeper understanding of the potential of optimization modeling to process information and build a knowledge base for adaptive management. The results highlight how management strategies could dynamically adjust to real-time ecological and hydrological data through optimization, enabling more responsive decision-making. Optimization outputs also help identify optimal timeframes for diversion goals, such as during significant flow variability or reduced ecological target performance. This work fills a crucial gap by advancing the operationalization of adaptive management and providing a framework applicable to diverse contexts and conditions.

Adaptive management often remains an aspirational concept, rarely translated into actionable practices. Chapters 3 and 4 address this challenge by providing a framework for operationalizing adaptive water management through optimization modeling. In Chapter 3, I focus on the immediate, point-scale application of optimization to current practices. In contrast, in Chapter 4, I expand the scope, by examining how optimization can support planning under future uncertainty and answering the last research question in the context of optimization modeling employment in adaptive management support. Building on insights from previous chapters about tailoring models to deliver actionable outputs, Chapter 4 further advances the research by integrating future environmental uncertainties—such as climate change and land use alterations—into optimization modeling for water resource management. Here, I have extended the methodology from Chapter 3 to the catchment scale and have examined the sustainability of the diversion under two future scenarios: one that reflects conventional land use practices and one that is based on an ecologically conscious strategy. These scenarios incorporated changes in land use/land cover and climate impacts on river hydrology, using historical data and future projections (2041–2070) for temperature and precipitation. The simulations revealed variations in water availability for human and environmental needs, emphasizing the importance of testing socio-environmental contexts to balance ecological health with water supply security.

The optimization modeling conducted in this chapter highlighted possible key management strategies, such as considering seasonal shifts and spatial variability in water availability, setting site-specific diversion targets, and prioritizing ecological needs during critical periods. It also demonstrated the potential of optimization to address the temporal and spatial complexities of water management under future uncertainties. Ultimately, I believe the main contribution of this chapter lies in providing essential insights into how optimization can guide management decisions in the face of changing resource availability.

5.2 Addressing scale in optimization models for water management

Scale is a foundational element in environmental models that integrate diverse data sources and disciplinary perspectives – consequently, there is a need for models that effectively balance the demands of detailed, site-specific management needs with broader, basin-wide strategies (Iwanaga et al., 2021). Furthermore, it is widely acknowledged that model inputs and outputs need to accurately reflect real-world management conditions in order to be effective (Pahl-Wostl, Palmer, et al., 2013). This is especially true for water management problems that aim at ecological preservation. However, the effort associated with achieving a reliable representation within optimization models is not sufficiently explored in the literature. In this thesis, I addressed the critical task of adequately representing both temporal and spatial scales in optimization models for water management. I found that, when developing optimization models, scaling decisions can pose a challenge for the modeler and significantly influence the model's ability to meet the requirements of the management context in target scaling. To enable better decision-making at the appropriate temporal and spatial scale of the model, I facilitated the model development process in Chapter 2 with a simple, step-by-step procedure that helps align the model scales with the real-world conditions of water management. While this structured approach aims to ensure that the choice of scale is systematically aligned with the specific requirements of the management context, the extent to which these scale decisions affect the model output remains to be fully quantified. In fact, the modeler's perspective and assumptions about the system can influence how they approach scale representation for a particular management issue (Iwanaga et al., 2021). To exploit the full potential of optimization modeling for water management problems and sustainable resource allocation, I believe it would be beneficial to further explore the impact of these scale-related modelers' beliefs.

Prioritizing data is essential to maintain model clarity while also obtaining the local insights needed for effective, fine-scale modeling (Loucks & Van Beek, 2017). I argue that the model development process directly influences the quality and type of data the model requires. For example, in Chapter 4, I considered different structuring approaches to enhance transparency and better align with ecosystem needs. A top-down approach, which limits daily diversions based on annual municipal demand, risks introducing uncertainties and may fall short of meeting ecosystem needs. In contrast, a bottom-up approach that matches e-flow requirements with available flow increases the likelihood of supporting ecosystem services and adapting to environmental changes. This example demonstrates how a bottom-up strategy can foster a more adaptable and resilient model structure. By carefully selecting the most relevant information, the model remains both manageable and responsive to localized needs, ultimately enhancing its applicability in real-world scenarios. My approach in Chapters 3 and 4 to reveal temporal changes and spatial variability of river water volumes available for diversion directly reflects this principle, underscoring that flexibility in adapting to changing spatial contexts is critical for maintaining reliable water management outputs. Building on this foundation, in Chapter 3, I developed an optimization model approach for a site-specific diversion target, focusing on isolated locations within the river. This pilot-scale application demonstrated how optimization can be used to support decision-making on small scales without overwhelming the process with excessive information needs.

For comparison, I extended this approach to a basin-wide spatial coverage in Chapter 4, merging information on adjacent river segments to display the whole river network. Although an optimization model can potentially address planning and management needs across multiple scales, my exploration pointed out a practical distinction in scale suitability based on the specific assessment objectives. Finer scales prove more effective for accurately capturing local hydrology and ecological requirements, allowing for detailed insights into site-specific dynamics and interventions. In contrast, larger scales are more appropriate for identifying overarching, long-term patterns, offering a strategic perspective that helps pinpoint management hotspots and guide broader planning decisions. This scale-wise distinction enhances the model's ability to balance detailed local needs with basin-wide management strategies, optimizing its utility across varying planning contexts. Collectively, this suggests that scale decisions within optimization models should be guided by strategies accommodating multiple management objectives across scales while maintaining model efficiency and simplicity. This multi-scale perspective aligns with the systems thinking of Thorp (2014) and Simonovic (2012), both of whom advocate that effective water management demands adaptable, cross-scale models capable of capturing both immediate and long-term management impacts. However, integrating various temporal and spatial scales within a single optimization model presents a significant modeling challenge (Horne et al., 2016). Overall, I believe that a well-designed optimization model must incorporate essential information across scales while keeping the decision-making process manageable during development. It is important to balance the need for detail at various scales with the simplicity of the model. If successful, the model can seamlessly integrate the needs of detailed, site-specific management and broader, basin-wide strategic objectives within a unified optimization framework that delivers an effective and practical output format.

Despite the contributions of this thesis, there are some challenges in integrating fine- and large-scale insights without oversimplifying their complexities, especially in river systems, where numerous interactions and processes occur simultaneously across multiple scales (Iwanaga et al., 2021). For example, the basin-scale model in Chapter 4 provides essential information on the spatial and temporal variability of optimized river flow across the network. However, it does not fully capture the feedbacks and synergies between river flow and ecosystem processes. This results in a lack of granularity needed for real-time, local decision-making on optimal environmental flow management actions. This mirrors the gaps identified by Gurnell et al. (2016), who argue for models that dynamically adjust across scales as new data and environmental changes arise. To address hierarchical and multi-layered management problems, I found that an adaptive, scale-flexible approach—where models adjust to changing contexts—could provide a solution that improves model responsiveness and resilience. This flexible approach reinforces the need for context-specific strategies in water management that simultaneously address both fine, site-specific needs and broader objectives at the watershed level.

The understanding of scale representation in optimization models for sustainable water management presented in this thesis echoes a broader call in the literature for improved scale integration within management strategies (Arthington et al., 2024; Poff et al., 2017). While the need for multi-scale integration and dynamic adaptation should be set as a future research goal, I emphasize that transparency should take precedence when synergies between data and modeling approaches cannot be achieved. Achieving this balance requires adherence to a rigorous, mutually agreed-upon set of model development steps to ensure adaptability and responsiveness to the inherent complexities of water management.

5.3 Incorporating environmental flows (e-flows) into optimization models

Environmental protection is increasingly recognized as a critical objective for water management (Finn & Jackson, 2011), especially as environmental pressures — such as climate change, population growth, and land use alterations—increase demands on water resources (Chowdhury & Das, 2024). The advancement of water management practices requires that e-flows become a core component of resource planning to ensure that, in addition to human needs, essential ecological processes are also supported (Arthington et al., 2024; Poff et al., 2017). I found that the wide range of approaches to incorporating e-flows into optimization models reflects the diversity of case studies and contexts in which they are applied. This diversity underscores the need for adaptable, standardized strategies for optimizing ecological and human demands within water management.

In Chapter 2, I identified several critical decisions that influence how environmental flows are defined in models. The choice of assessment locations, spatial scale, and approach to defining e-flows proved essential to accurately reflecting ecological conditions. Often, the success of these decisions depends on the availability of historical and real-time data from monitoring stations. Monitoring networks are essential for developing effective e-flow models for different management contexts (Poff et al., 2007). For instance, an extensive network of gauging stations can provide crucial information in complex river systems with multiple reservoirs. It can capture spatial and temporal flow variability across the basin, enhancing the model's capacity to represent ecological impacts accurately. Flow magnitude parameters are commonly used as hydrological indicators to assess the state of ecosystems, with monthly and annual flow readings providing valuable insights into seasonal cycles. However, these general metrics sometimes lack the level of detail needed for more refined ecological assessments. To improve accuracy for localized applications, breaking down large river flow rates into site-specific values can increase model accuracy when assessing ecosystem response (Cai & Zhang, 2018).

Defining e-flow requirements based on empirical data related to specific habitats or species can be convenient for finer-scale or short-term assessments. Techniques such as regression modeling and hydro-ecological tools (such as PHABSIM, Bovee et al., 1998) allow for the establishment of minimum flows for critical ecological functions. While these methods increase ecological relevance, they are data-intensive and may be challenging to implement across diverse habitats or settings (Davies et al., 2014). In more complex scenarios, participatory methods can provide a way to define hydrological thresholds by directly involving stakeholders in the decision-making process. This stakeholder engagement is invaluable for developing models that accurately reflect local needs and knowledge (Ananda & Proctor, 2013). Such an approach benefits optimization models targeted at systems with multiple environmental and human assets and high spatial complexity, allowing for more adaptive and inclusive management strategies. Furthermore, some studies incorporate broader flow indicators, such as baseflow conditions and, occasionally, water quality parameters like temperature and dissolved oxygen levels. Although less common, these indicators provide valuable insights when flow regime changes directly impact ecosystem health.

A reliable representation of ecological freshwater flow requirements is essential for generating robust optimization assessment results. Expert knowledge offers the opportunity to gain substantial insights (Nelitz et al., 2015). Incorporating the latest freshwater ecology and eco-hydrology advancements validates our understanding of ecological flows. However, the lack of a standardized method to directly translate this expertise into input parameters for optimization models creates a gap between environmental expertise and model integration. In response to this, I presented a practical approach in Chapters 3 and 4 that builds on the insights from Chapter 2. This approach demonstrates that combining site-specific hydrological data with basin-wide environmental flow parameters can effectively meet both localized and broader ecological needs within a cohesive modeling framework. This method allows expert knowledge of ecological requirements to be elicited and integrated into an optimization model for the case study. Importantly, it avoids data over-processing and allows for stepwise model refinement as new insights or data become available. By varying hydrological thresholds across multiple model runs, this approach can help identify sustainable water diversion volumes with increased predictive accuracy, demonstrating the potential of flexible modeling for ecological flow management. Despite these advantages, a significant limitation remains in the resource demands of the approach presented in Chapters 3 and 4. First, the iterative simulations require stakeholder commitment to repeated model runs, which may demand more time and investment than conventional static approaches. This need for stakeholder engagement underscores the collaborative nature of adaptive water management and highlights a key area for further development, namely, fostering stakeholder support for resource-intensive but ultimately more accurate modeling techniques.

Another challenge is related to the complexity of representing dynamic ecological systems within static optimization constraints. E-flows are inherently variable; in fact, ecological needs shift with seasonal changes, extreme weather events, and long-term environmental changes such as climate change. By defining e-flows as fixed constraints, there is a risk of oversimplifying the complexity of ecological processes, which may reduce the model's effectiveness under unforeseen conditions. My findings suggest that overcoming this gap requires prioritizing certain data types, carefully selecting model parameters, and accepting trade-offs between detail and manageability—choices that inevitably shape model accuracy and relevance (Badham et al., 2019; Iwanaga et al., 2021).

Balancing hydrological detail with data feasibility in incorporating environmental flows (e-flows) into optimization models creates a foundation for sustainable water management that prioritizes ecological integrity. This research underscores a shift from output-focused modeling to a more integrated, process-driven approach incorporating ecological constraints within a flexible framework. By setting hydrological constraints, we prioritize e-flows, safeguarding key ecological functions while meeting human water demands. Selecting spatial and temporal scales that capture both local and basin-wide dynamics should ensure that models remain responsive to diverse ecological needs. Finally, incorporating adaptive and participatory elements fosters a modeling process that not only reflects local knowledge but also strengthens resilience to environmental change. Through these guiding principles, we create optimization models capable of addressing the complex interplay between ecological preservation and water management and support a robust and inclusive approach to sustainable resource planning.

5.4 Using optimization models as a tool in support of adaptive water management implementation

Adaptive management is a dynamic yet composite management paradigm that is increasingly recognized as essential to the management of complex water systems because it provides a proactive approach to addressing uncertainty associated with factors such as climate variability, population growth, and land use modifications (Allan & Watts, 2018; Delavari Edalat & Abdi, 2018). However, despite a few examples of successful applications worldwide (for instance, see Failing et al., 2013; Smith, 2011), implementing adaptive management in water resource management remains challenging. Some key obstacles include the need for polycentric governance, organizational flexibility, and public participation—integral components of “social learning” strategies—alongside balancing ecological and human demands, limited data availability, fragmented governance and monitoring efforts, and difficulties in adjusting strategies in real-time. Furthermore, the lack of standardized methodologies for iterative, adaptive management continues to hinder implementation (Delavari Edalat & Abdi, 2018; Wan Rosely & Voulvoulis, 2024; Webb, Watts, et al., 2017). Data limitations, for instance, constrain the level of detail with which ecological conditions can be monitored. At the same time, institutional and regulatory rigidity can prevent the shift toward more adaptive frameworks (Pahl-Wostl, 2006). Furthermore, the intricate, non-linear nature of ecological systems introduces uncertainties that complicate any predictive modeling, leading some managers to rely on more traditional, static approaches (Poff & Zimmerman, 2010).

As shown in Chapter 2, optimization modeling fits well with the adaptive management cycle, particularly before the implementation stage. I have found it can be applied within both the inner and outer feedback loops of the adaptive cycle (i.e., the “Plan-do-monitor-learn” process as described by Webb, Watts, et al., 2017). Optimization modeling employment specifically can provide insights into where and to what extent changes may occur, as well as identify priority areas for targeted monitoring in the short term. In the long term, it can enhance the adaptability of water management frameworks, positioning optimization as a valuable tool for anticipating and responding to environmental changes in a structured, iterative manner.

Water managers need data that empowers them to make adaptive, informed choices that align with the scale and priorities of the management plans. In the chapters presented, I showed how optimization modeling can be useful for several adaptive management challenges by strengthening decision-making frameworks, promoting transparency, integrating preference-defined thresholds, enabling scenario-based planning, and providing a structured approach to balancing ecological and human demands. The insights from the exploratory optimization assessments presented in Chapters 3 and 4 reveal that optimization modeling can be employed not only to aid in forecasting trade-off outcomes—such as those related to water allocation for specific ecological objectives—but also to discover patterns and pinpoint optimal locations or timeframes for targeted interventions. To demonstrate how optimization can inform adaptive management, I took an unconventional data-driven approach in both chapters by running optimization simulations at two different scales within the same case study. By recurring to different water management scenarios at basin-wide scales, I was able to leverage empirical data to reveal optimal patterns for water diversion, identify critical "hotspots", and make evidence-based recommendations for scale-sensitive water resource management needs directly supporting adaptive management-oriented decision-making. As a result, I identified two primary goals for employing optimization modeling in water management for adaptive planning, specifically in the context of river flow diversion. First, simulations under present flow conditions are particularly suited to fine-scale applications (Chapter 3) by accommodating short-term changes such as seasonal variations or extreme weather events, as they allow for refining or adjusting water supply decisions, environmental thresholds, and the range of species or ecological endpoints considered. This is particularly relevant in contexts where limited data and high stakeholder involvement necessitate clear and negotiable trade-offs (Loucks & Van Beek, 2017). Second, simulations under future scenarios (Chapter 4) that encompass climate change and land use alterations provide the opportunity to highlight key areas for prospective monitoring, addressing the need to screen larger regions and focus on priority zones. This information offers the chance to address long-term environmental stressors, ensuring that management objectives remain relevant across temporal scales.

Participatory approaches are critical for adaptive management to build acceptance and reflect the knowledge of local communities and stakeholders, who can help refine e-flow thresholds based on observed ecological and social impacts (Ananda & Proctor, 2013). In this thesis, I have provided evidence that optimization supports the critical aspect of stakeholder engagement in adaptive management, as demonstrated by the bottom-up approach in Chapter 4. Additionally, optimization modeling offers a practical solution to the iterative nature of adaptive management. By designing models that support incremental refinement as new data becomes available, as seen in Chapters 3 and 4, water managers can update and improve models based on recent findings, maintaining their relevance. This aligns with the adaptive management principle of learning from each planning cycle, helping to ensure that optimization models remain aligned with actual conditions and management objectives. This incremental, data-driven refinement is essential to overcome the resistance to iterative approaches in water management, often perceived as inefficient or resource-intensive (Gunderson & Holling, 2002).

Based on the research conducted, I have identified several principles for using optimization models to support adaptive water management implementation. First, integrating flexible thresholds for e-flows ensures adaptability to short-term changes, while scenario-based planning prepares for long-term shifts. Second, prioritizing site-specific data collection through a robust gauging network enhances model accuracy in assessing ecological responses. Third, engaging field experts in model development, as demonstrated in Chapter 4, fosters responsive, context-sensitive models that align with local ecological needs. Additionally, establishing an iterative model update process helps keep models relevant as new data emerges. Finally, investing in computational resources and training is essential to manage the complexities of adaptive optimization modeling effectively. Overall, this research adds valuable evidence on how optimization can provide a responsive, transparent, and scalable framework capable of adapting to evolving conditions and shifting management priorities.

5.5 Limitations of this work

In considering the research approach and methodology employed in Chapters 2, 3, and 4, I acknowledge certain limitations and shortcomings that, while potentially relevant for the relevance and generalizability of my work, do not undermine the validity or intent of the approach taken. A key factor underlying most of these limitations is the lack of "high-power" stakeholder engagement, such as the Cantabrian water management authorities, which prevented the translation of the modeling output into actions. In fact, the optimization simulations conducted for Chapters 3 and 4 remain at the proof-of-concept level without progressing to real-world implementation or monitoring stages. Ideally, these types of modeling simulations in support of water resource management decisions should be extended to include practical application and feedback loops, allowing the models to be tested, refined, and validated against actual outcomes (Kergus et al., 2022). Such an approach is fundamental in adaptive management, where iterative learning and adjustments based on real-world feedback are key to addressing the dynamic and evolving challenges of water management. I recognize that the absence of this crucial stage prevents the optimization modeling conducted in this thesis from fully validating its usefulness in effectively informing river water diversion planning.

The thesis also omits a formal sensitivity and uncertainty assessment, which could have improved the robustness of the optimization models. While sensitivity analysis could identify critical parameters influencing outcomes, and uncertainty assessments could reveal the range of potential results under varying conditions – such as input data, ecological thresholds, or future climate projections – the focus of this work was to demonstrate conceptual applications rather than provide absolute results, as highlighted in Chapter 3. I prioritized developing and testing methodological frameworks over detailed parametric evaluation. Nevertheless, the presented results can still stimulate discussion among relevant stakeholders. Future work should incorporate these assessments to improve model reliability and its capacity to inform adaptive decision-making.

Furthermore, regarding the optimization results, I deliberately adopted a preference-neutral approach in both Chapters 3 and 4, averaging outcomes such as objective scores across various scenarios to produce a simplified, ready-to-use hydrograph for daily river flow diversions. This approach aimed to prioritize usability and accessibility, offering decision-makers a straightforward, optimal solution without requiring extensive engagement during the modeling phase. As Miettinen (1998) noted, no-preference methods are suitable when decision-makers lack predefined expectations or are satisfied with any optimal solution, partially justifying my intent of prioritizing practicality and immediate applicability. However, optimization models inherently generate a range of optimal solutions that stimulate discussion, ideally requiring stakeholders to review and select to align with specific management goals. While stakeholder input was not incorporated due to the exploratory nature of this research, this presents an exciting opportunity for future work to enhance inclusivity and transparency in adaptive water management.

Additionally, the research is based on a single case study—the Pas River basin in Northern Spain—focused on river flow regulation for water diversion, with fixed thresholds for environmental flows set on local species. While this focus allowed for a detailed exploration, it narrowed the model's adaptability and generalizability. Expanding to different river and flow alteration systems would have added valuable data and helped verify the relevance and flexibility of the model under varying ecological and socio-economic conditions. Furthermore, allowing thresholds to vary or to be defined in part by stakeholders would have aligned the optimization models more closely with adaptive management's emphasis on context-specific, participatory approaches. This choice might have improved the optimization model's responsiveness to the particular ecological and social dynamics influencing water management decisions in different contexts.

Finally, I must acknowledge that the optimization assessments performed are relatively simple, particularly with respect to the conceptual model of actual management objectives and targets for the Pas River water diversion, which considered only a few ecological endpoints. This simplification means that the models may not fully reflect the true variability and complexity of the ecological processes and interactions critical to sustainable water management. A more sophisticated ecological model, with a larger number of hydrological parameters representing various biological and environmental interactions with the river flow, would have offered a richer understanding of how these systems respond to different diversion scenarios ultimately improving its utility for adaptive management.

Thus, the representation of the ecosystem could have been limited, which, in turn, limited the depth and accuracy of my findings.

5.6 Recommendations: generalizable principles for optimization modeling to support water resource management

With this work, I have laid a foundation for the design and application of optimization models to advance water resource management practices toward an adaptive management framework, as demonstrated in Chapters 2, 3, and 4. Building on the insights and findings from these chapters, I propose several overarching recommendations to guide both modelers and water managers in developing robust, flexible, and sustainable optimization models. These recommendations are also intended to support managers in formulating strategies that effectively address the complexities of water resource system representation:

(i) Defining clear boundaries and scales: Setting explicit spatial and temporal boundaries within optimization models is crucial for ensuring relevance and transparency. As emphasized in Chapter 2, clearly communicating the optimization problem statement throughout the problem perception and formulation phases enhances system understanding, facilitates stakeholder engagement, and ensures that trade-offs are assessed at appropriate scales;

(ii) Enhancing model transparency and clarity: A framework for optimization model development, as presented in Chapter 2, offers a systematic approach to clarifying system conceptualization. Answering key questions for each optimization phase — including physical systems, hydrological states, objective functions, and constraints — ensures that input data and objectives align with management goals, thereby improving model transparency;

(iii) Considering scale-sensitive approaches: As demonstrated in Chapter 4, assessments at the basin level are effective for identifying hotspots of reduced water availability and for testing large-scale management scenarios. Conversely, the reach-scale modeling, explored in Chapter 3, refines site-specific objectives and assesses localized trade-offs. By using these approaches within a single framework, managers can effectively address both broad ecological and human needs and localized priorities;

(iv) Prioritizing environmental flow representation: Optimization models should prioritize ecological endpoints based on hydrological requirements for key species or ecosystem services, as shown in Chapters 3 and 4. Expanding the range of ecological components and considering long-term adaptation potential are essential for improving ecological accuracy and relevance. Applying appropriate distinction within the optimization model to prioritize species' needs upstream versus downstream could address ecosystem variability throughout the river network;

(v) Enhancing input data quality and results communication: Reliable input data and clear communication of optimization results are critical for decision-making. Addressing uncertainty in output data (e.g., by using multiple scenarios), improving used data resolution (e.g., by relying on gauging networks), and focusing on standardized ecological indicators can reduce epistemic and systemic uncertainties. The decision to communicate results in user-friendly formats such as hydrographs can improve acceptance among decision-makers.

5.7 Overall thesis conclusions

Optimization modeling for water resource management has gained significant momentum due to advancements in computational methods and the growing need to balance human and ecological water demands. This thesis builds on this interest and demonstrates the flexibility and potential of optimization models as a tool for addressing the complex challenges of sustainable water management. I have shown that optimization models can inform day-to-day decision-making and equip managers with the appropriate spatial-temporal information to anticipate future risks to optimal water resource availability—all while being accessible due to low cost and minimal training requirements. However, the possibilities go beyond purely technical applications and offer an opportunity to rethink and implement water management within an adaptive management framework. My results show how optimization can be an integral component of the adaptive water management cycle, providing insights before pre-implementation and using its inherent flexibility to integrate scenarios that account for evolving environmental conditions caused by climate and land use change. By addressing critical gaps — such as trade-offs in scale representation, the integration of environmental flows (e-flows) into optimization models across scales, and their applicability at the catchment scale under future environmental changes — I have provided a basis for a broader application of optimization modeling in different management contexts. This will enable the identification of critical hotspots for intervention, the adaptation of water allocation strategies to seasonal and long-term climate scenarios, and the integration of knowledge-based preferences to balance ecological and human needs. By advancing these methods, optimization modeling can strengthen decision-making processes, improve their reliability and effectiveness, and ultimately serve as a blueprint for managing water resources in dynamic, stratified systems.

5.8 Future research needs

In Chapter 2, I proposed a framework to navigate option selection relative to scale when developing optimization models. In order to further advance the application of optimization modeling in water resource management, future research should focus on developing an integrated optimization framework to guide researchers and practitioners through the various stages of adaptive management across multiple scales. As emphasized by Horne et al. (2022), modular frameworks for optimization modeling can provide the flexibility needed to align with diverse management objectives and spatial contexts, offering a structured yet adaptable toolset for addressing water management challenges. Achieving this could be further supported by scaling up assessments across diverse case studies, tailoring approaches to different management contexts, and integrating stakeholder-defined thresholds and preferences. These efforts would enhance the generalizability and inclusivity of optimization models, ensuring they align more effectively with the principles of adaptive management.

Additionally, uncertainty remains a persistent challenge in water management modeling, as highlighted by Judd, Boese, et al., (2023) and Judd, Horne, et al., (2023). In my work, I did not explicitly focus on uncertainty quantification. Future research should hence explore innovative methods to navigate and represent uncertainty within optimization models, such as sensitivity analyses, scenario-based modeling, and probabilistic frameworks. These tools can enable optimization models to capture better and communicate the inherent variability in hydrological, ecological, and socio-economic systems, increasing the robustness and credibility of modeling outcomes for adaptive management.

In Chapter 4, I tested a spatially explicit optimization model output underscoring the importance of alternative conceptualizations of management systems, particularly during the problem perception phase. This could enhance the ability of optimization models to address complexities inherent in stratified socio-ecological systems. Spatially explicit optimization models, already prevalent in land-use management (Li et al., 2023), hold great potential for water management by revealing multi-scale interactions and trade-offs. Extending this work to incorporate more sophisticated ecological parameters, detailed land-use patterns, and dynamic climate scenarios, as suggested by Judd, Boese, et al., (2023), could improve the ability of optimization systems to address complexities inherent in stratified socio-ecological systems. Moving toward temporally explicit models that account for seasonal or event-driven variability would also strengthen their applicability in adaptive management. Furthermore, Judd et al., (2022) also emphasize the importance of integrating climate resilience into ecological flow objectives—an essential consideration for supporting long-term water management under uncertain and shifting climatic conditions.

Finally, establishing stronger links between optimization systems and monitoring plans is equally crucial. As noted by Judd et al., (2022) establishing clear connections between modeled e-flow endpoints and monitoring frameworks can bridge the gap between theoretical modeling and practical application, enabling iterative feedback loops. These loops are central to adaptive management, where real-world validation is essential for refining and improving optimization outputs. These advancements would collectively position optimization modeling as a convenient and flexible tool for adaptive water management, capable of addressing evolving challenges while fostering sustainable and resilient resource use.

Appendix A

Table A1 **Summary of reviewed studies**. Legend: /=no info, MP=mathematical programming, S=stochastic, MAG-d=magnitude of daily and sub-daily flows, MAG-m=magnitude of monthly and yearly flows, MAG/DUR-ext=magnitude and duration of extreme water conditions, FREQ/DUR-pulses=frequency anFigure 15 **Optimization runs.** Comparison of the results for each run of the optimization model showing the pattern of the normalized average daily diversion percentage values (expressed as the daily percentage of the natural daily discharge). Yellow

Reference	Study system location	Management purpose	Targeted scale		Planning period	Solution method	Hydrological indicators	Objectives		Constraints	Trade-offs	Scenarios
			Spatial	Temporal				≤ 3	≥ 4			
(Arslan, 2015)	Aksu River Basin (Turkey)	energy production, ecological health	River	Sub-daily	/	MP-based	MAG-m	•		physical-environmental, infrastructure-related, supply-related, ecological	/	x
(Chen and Olden, 2017)	San Juan River, (Colorado River tributary, US)	disturbance reduction, ecological health	River section	Seasonal	3-year plan	MP-based	MAG-d	•		physical-environmental, infrastructure-related, supply-related	G	x
(Dai et al., 2017)	Three Gorges-Gezhouba reservoirs, Yangtze River (China)	energy production, ecological health	Multi-Reservoir	Seasonal	/	S	MAG-d	•		physical-environmental, infrastructure-related	G	x
(Fallah-Mehdipour, Bozorg-Haddad and Loáiciga, 2018)	Karoon IV dam on Karoon River (Iran)	energy production, ecological health	Reservoir	Daily	/	MP-based / S	/	•		physical-environmental, infrastructure-related	G	/
(Fleifle et al., 2014)	El-Qalaa River, Nile River (Egypt)	functional purpose, ecological health	Sub-basin	Seasonal	/	S	NH	•		physical-environmental, supply-related, ecological	G	/
(Torabi Haghighi and Kløve, 2015)	Bakhtegan catchment (Iran)	disturbance reduction	River basin	Monthly	Intra-annual	MP-based	MAG-m	•		supply-related, ecological	G	x

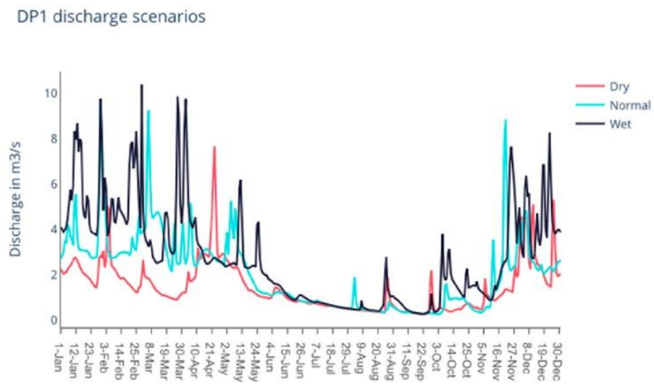
(Hassanjabbar, Saghafian and Jamali, 2018)	Karkheh Basin (Iran, Iraq border)	energy production, disturbance reduction	Multi-reservoir	Monthly	Annual	S	MAG-d, MAG/DUR-ext, FREQ/DUR-pulses	•		physical-environmental, infrastructure-related, supply-related	/	x
(Lewis and Randall, 2017)	Murrumbidgee River Irrigation Area (Australia)	functional purpose, ecological health	River basin	Monthly	Annual	S	MAG-m	•		physical-environmental, infrastructure-related, supply-related, ecological	G	X
(Martin et al., 2017)	Goulburn-Broken River catchment (Murray–Darling Basin, Australia)	functional purpose	Sub-basin	Daily	/	S	MAG-m			/	G	/
(Mullick, Babel and Perret, 2013)	Teesta River (Bangladesh)	functional purpose	River section	Monthly	Annual	MP-based	MAG-m		•	physical-environmental, ecological	T	x
(Paredes-Arquiola et al., 2013)	Duero River basin (Spain)	consumptive use, ecological health	River Basin	Monthly	Annual	/	MAG-m		•	supply-related	G	/
(Porse, Sandoval-Solis and Lane, 2015)	Luis L. Leon reservoir, Big Bend region of the Rio Grande/Bravo (Mexico-US)	ecological health	Reservoir	Monthly	/	MP-based	MAG-d, MAG-m, FREQ/DUR-pulses		•	physical-environmental, infrastructure-related, supply-related	DF	/
(Schlüter et al., 2005)	Amudarya River Basin (Central Asia)	consumptive use, disturbance reduction	Multi-reach	Monthly	Annual	MP-based	MAG-m			physical-environmental, infrastructure-related, supply-related, ecological	/	x
(Shang, 2015)	Ertix River / Ebinur Lake (Xinjiang, China)	consumptive use, ecological health	River section / Lake	Monthly	/	MP-based	MAG-m		•	infrastructure-related	G	/

(Shiau and Chou, 2016)	Hsintien Creek (Taiwan)	consumptive use, energy production, safety, disturbance reduction	River basin	Daily	/	S	MAG-m, MAG/DUR-ext, NH		physical-environmental, infrastructure-related	T	x
(Shiau and Wu, 2013)	Feitsui Reservoir (Taiwan)	consumptive use, energy production, safety, disturbance reduction	Multi-reach / Multi-reservoir	Sub-daily	Annual / Multi-annual	S	MAG-d, MAG/DUR-ext, RAT/FREQ-change		physical-environmental, infrastructure-related	G	x
(Szemis et al., 2012)	Murray-Darling River (Australia)	/	Reservoir	Monthly	Multi-annual	S	MAG-d, FREQ/DUR-pulses	•	physical-environmental, infrastructure-related	DF	x
(Szemis et al., 2013)	Murray-Darling River (Australia)	/	Reservoir	Monthly	Multi-annual	S	MAG-d, FREQ/DUR-pulses	•	physical-environmental, infrastructure-related	DF	x
(Szemis et al., 2014)	Murray-Darling River (Australia)	/	Reservoir	Monthly	Multi-annual	S	MAG-d, FREQ/DUR-pulses	•	physical-environmental, infrastructure-related	DF	x
(Steinschneider et al., 2014)	Connecticut River (New England, US)	disturbance reduction	River basin	Daily	Annual	MP-based	MAG-d, MAG-m	•	physical-environmental, infrastructure-related, supply-related, ecological	PF	x
(Suen and Eheart, 2006)	Dahan River Basin (Taiwan)	consumptive use, energy production, ecological health	River basin	Monthly	/	S	FREQ/DUR-pulses, TIM-ext	•	physical-environmental, infrastructure-related	PF	/
(Wang et al., 2015)	Philpott dam on Smith River (US)	consumptive use, energy production, disturbance reduction	Reservoir	Daily	Monthly	MP-based	MAG-m, MAG/DUR-ext	•	physical-environmental, infrastructure-related, supply-related, process-based	G	x

(Xevi and Khan, 2005)	Berembed Weir, Murrumbidgee River (Australia)	consumptive use	Multi-reach	Monthly	Seasonal	MP-based	MAG-m	•	physical-environmental, infrastructure-related, ecological	T	x
(Xu et al., 2017)	Han River, Yangtze River tributary (China)	consumptive use, energy production, disturbance reduction, ecological health	River	Daily	/	S	NH		physical-environmental, infrastructure-related, supply-related, ecological	DF	/
(Yin, Yang and Petts, 2012)	Tanghe Reservoir on the Tang River (China)	disturbance reduction	Reservoir	Daily	Annual	S	MAG-d, FREQ/DUR-pulses, RAT/FREQ-change	•	physical-environmental, supply-related	DF	/
(Yin, Yang and Liu, 2014)	Wangkuai Reservoir (Hai River basin, China)	disturbance reduction	Reservoir	Monthly	Annual	S	MAG-d, FREQ/DUR-pulses	•	physical-environmental, infrastructure-related, supply-related, process-based	DF	x
(Yin et al., 2015)	Wangkuai Reservoir, Hai River basin (China)	energy production	Reservoir	Monthly	Annual	S	MAG-d	•	infrastructure-related, supply-related, ecological	G, T	/

Appendix B

Supplementary Materials



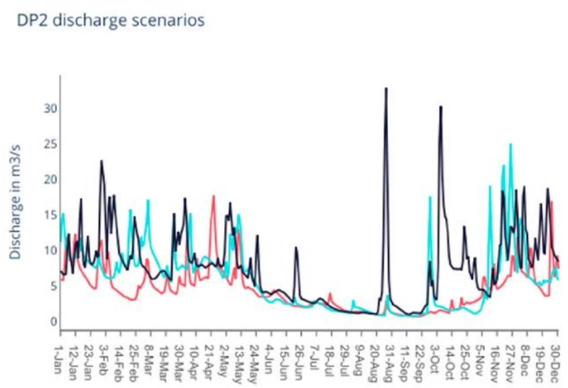


Figure S1. Hydrological time series used as representative discharge scenarios for the considered diversion points (DP1 and DP2).

a)

b)

c)

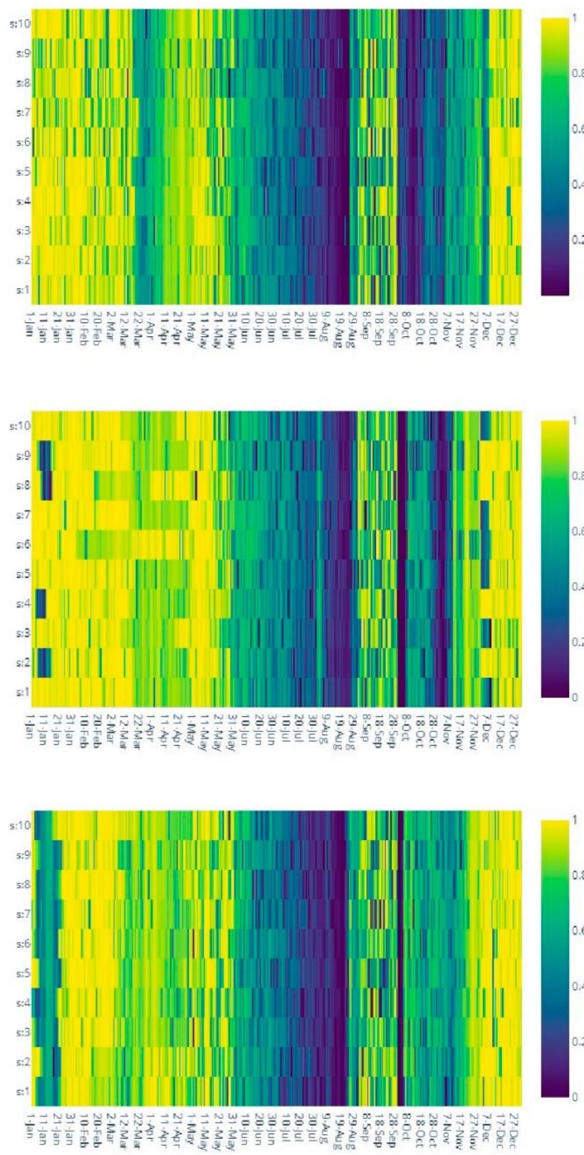


Figure S2. Combination of the average daily diversion percentages with respect to the natural discharge normalized to 0-1 range for each single run of the model ('s1-s10') under the same scenario. Yellow (1) tiles correspond with the highest diversion percentage, whereas blue (0) tiles correspond with the lowest optimal diversion. **Results for DP1** under dry (a), normal (b) and wet (c) scenarios.

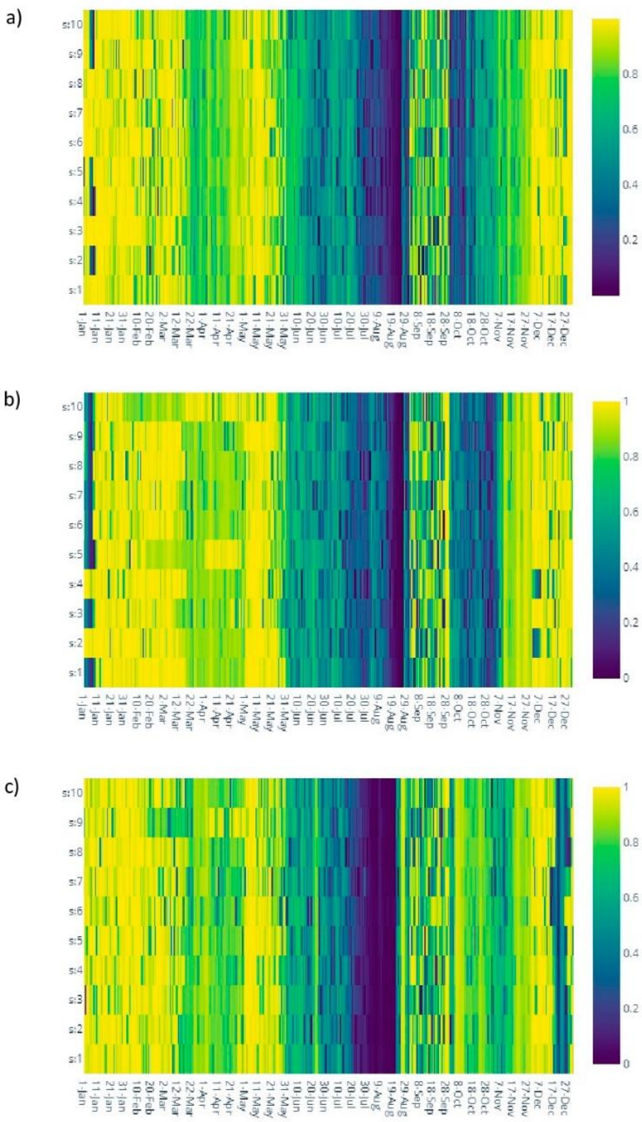


Figure S3. Combination of the average daily diversion percentages with respect to the natural discharge normalized to 0-1 range for each single run of the model ('s1-s10') under the same scenario. Yellow (1) tiles correspond with the highest diversion percentage, whereas blue (0) tiles correspond with the lowest optimal diversion. **Results for DP2** under dry (a), normal (b) and wet (c) scenarios.

a)
b)
c)

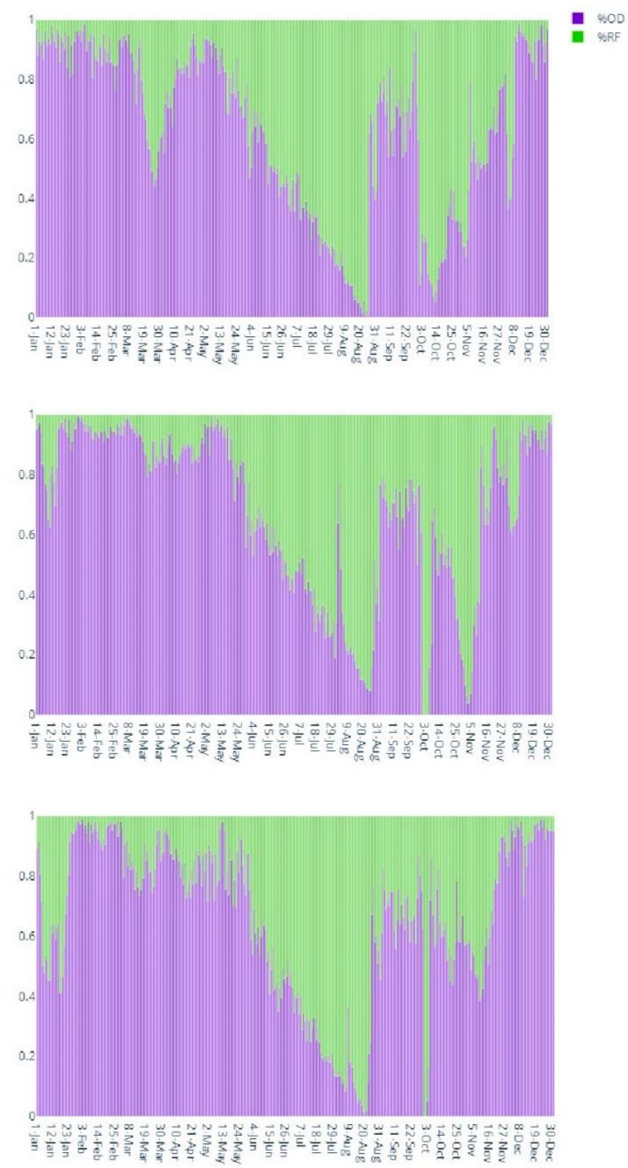


Figure S4. Barchart showing the normalized fraction (expressed in %) of discharge that has been optimized for abstraction (purple 'OD' bars) with respect to the natural flow (green 'RF' bars) at the daily scale. The diverted discharge is calculated as a daily average for all the 10 runs of the model for each scenario. **Results for DP1** under dry (a), normal (b) and wet (c) scenarios.

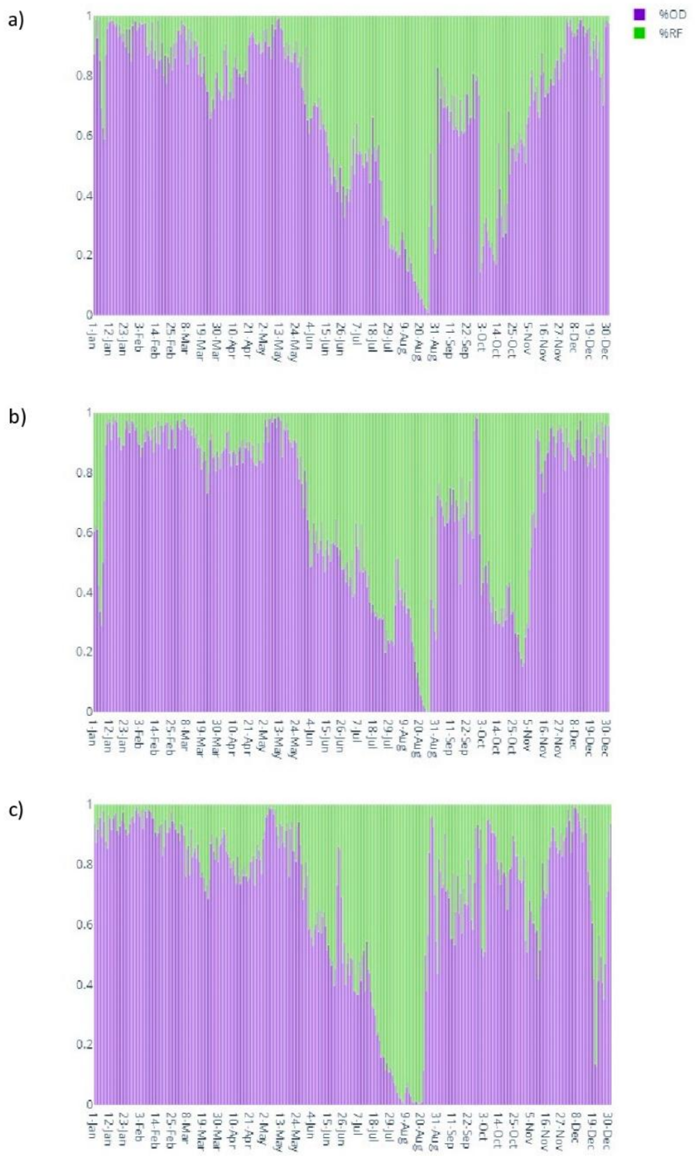


Figure S5. Barchart showing the normalized fraction (expressed in %) of discharge that has been optimized for abstraction (purple 'OD' bars) with respect to the natural flow (green 'RF' bars) at the daily scale. The diverted discharge is calculated as a daily average for all the 10 runs of the model for each scenario. **Results for DP2** under dry (a), normal (b) and wet (c) scenarios.

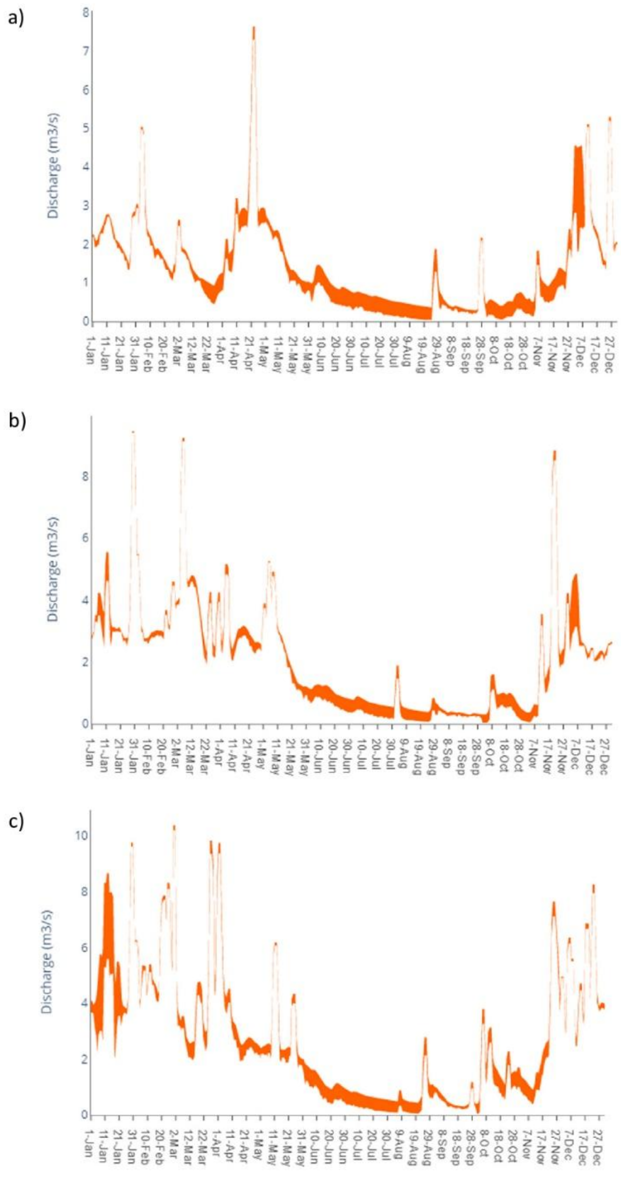


Figure S6. Flow series showing the magnitude of gap between the daily optimized diverted discharges in m^3/s with respect to the natural discharge. Greater thickness indicates the highest trade-off between the natural discharge and water for municipal use. **Results for DP1** under dry (a), normal (b) and wet (c) scenarios.

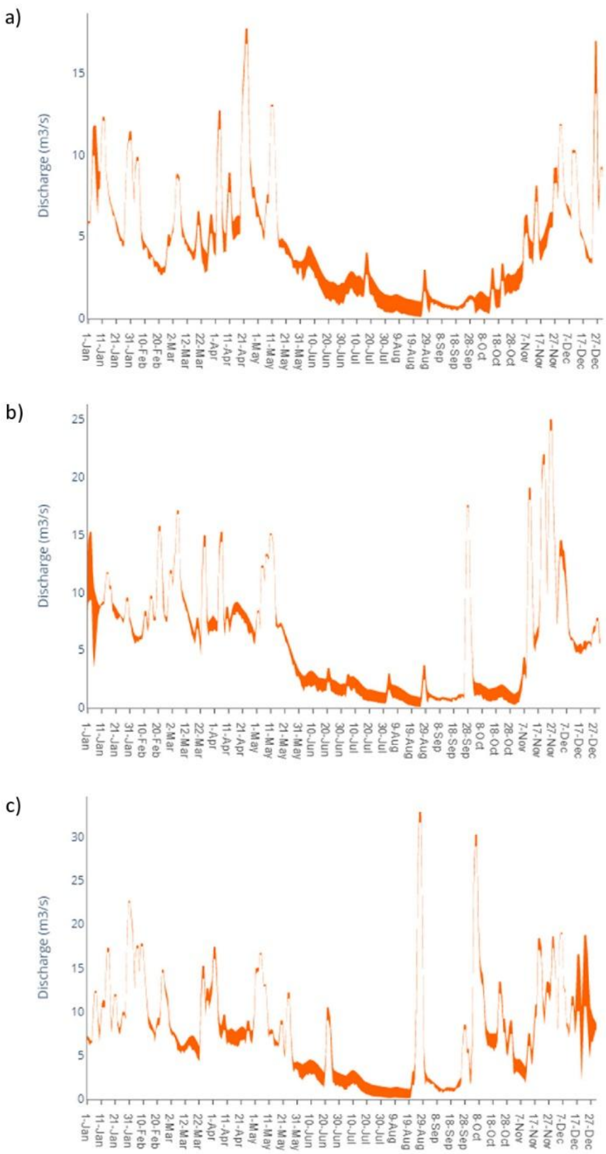


Figure S7. Flow series showing the magnitude of gap between the daily optimized diverted discharges in m^3/s with respect to the natural discharge. Greater thickness indicates the highest trade-off between the natural discharge and water for municipal use. **Results for DP2** under dry (a), normal (b) and wet (c) scenarios.

Table S1 Average objective function score (municipal water demand), for each simulation run (1-10). The score indicate the achievement of the objective (minus sign) and the ratio of the resulting supply after optimization to the required supply (i.e. the proportion of existing water for human consumption with respect to demanded water; AVG, MIN and MAX values refer to the average, minimum and maximum value for each set, respectively. **Results for the DP1** under dry, normal and wet scenarios.

	DP1		
RUN:	**Dry**	**Normal**	**Wet**
1	-134.14	-209.57	-266.20
2	-134.34	-204.36	-271.45
3	-136.62	-208.30	-268.61
4	-137.05	-209.96	-263.14
5	-134.76	-209.25	-273.09
6	-133.21	-210.18	-264.93
7	-132.31	-212.78	-268.04
8	-127.97	-208.82	-272.77
9	-129.91	-206.23	-264.72
10	-133.64	-208.50	-275.35
AVG	-133.40	-208.79	-268.83
MIN	-127.97	-204.36	-263.14
MAX	-137	-213	-275

Table S2 Average objective function score (municipal water demand), for each simulation run (1-10). The score indicate the achievement of the objective (minus sign) and the ratio of the resulting supply after optimization to the required supply (i.e. the proportion of existing water for human consumption with respect to demanded water; AVG, MIN and MAX values refer to the average, minimum and maximum value for each set, respectively. **Results for the DP2** under dry, normal and wet scenarios.

	DP2		
RUN:	**Dry**	**Normal**	**Wet**
1	-172.09	-234.62	-299.99
2	-170.52	-234.34	-296.80
3	-175.62	-228.17	-298.36
4	-171.66	-232.57	-298.00
5	-173.92	-231.20	-295.49
6	-173.71	-231.62	-293.23
7	-174.54	-227.52	-288.43
8	-172.89	-231.38	-295.89
9	-173.13	-231.16	-291.14
10	-171.13	-227.95	-295.75
AVG	-172.92	-231.05	-295.31
MIN	-170.52	-227.52	-288.43
MAX	-176	-235	-300

Dry Scenario – DP1						
RUN:	R1	R2	R3	R4	R5	R6
1	0.01	0.79	0.24	0.01	0	0.10
2	0.01	0.79	0.20	0.01	0	0.07
3	0.02	0.75	0.20	0.01	0	0.11
4	0.01	0.80	0.20	0.01	0	0.08
5	0.01	0.79	0.17	0.01	0	0.10
6	0.01	0.79	0.23	0.01	0	0.07
7	0.01	0.80	0.31	0.01	0	0.11
8	0.01	0.80	0.25	0.01	0	0.13
9	0.01	0.83	0.21	0.01	0	0.10
10	0.01	0.75	0.19	0.01	0	0.07
TEST	0	0.67	0	0	0	0
AVG	0.01	0.79	0.22	0.01	0	0.09
MIN	0.01	0.75	0.17	0.01	0	0.07
MAX	0.02	0.83	0.31	0.01	0	0.13

Tables S3-S4-S5 Average objective function scores (R1-R6), for each simulation run (1-10). TEST values refer to the test runs on the undisturbed hydrograph; AVG, MIN and MAX values refer to the average, minimum and maximum value for each set, respectively. **Results for the DP1** under dry, normal and wet scenarios.

Normal Scenario – DP1						
RUN:	R1	R2	R3	R4	R5	R6
1	0.01	0.73	0.17	0.01	0	0.08
2	0.02	0.63	0.15	0.01	0	0.07
3	0.02	0.73	0.24	0.00	0	0.12
4	0.02	0.68	0.14	0.01	0	0.06
5	0.03	0.75	0.21	0.01	0	0.10
6	0.02	0.72	0.19	0.01	0	0.08
7	0.02	0.73	0.12	0.01	0	0.08
8	0.01	0.67	0.18	0.01	0	0.06
9	0.02	0.66	0.19	0.01	0	0.08
10	0.02	0.69	0.15	0.00	0	0.05
TEST	0	0.10	0	0	0	0
AVG	0.02	0.70	0.17	0.01	0	0.08
MIN	0.01	0.63	0.12	0	0	0.05
MAX	0.03	0.75	0.24	0.01	0	0.12

Wet Scenario – DP1						
RUN:	R1	R2	R3	R4	R5	R6
1	0.01	0.28	0.18	0.01	0	0.02
2	0.01	0.39	0.19	0.01	0	0.08
3	0.01	0.26	0.15	0.01	0	0.01
4	0.01	0.26	0.12	0.00	0	0.04
5	0.01	0.32	0.17	0.01	0	0.04
6	0.01	0.35	0.14	0.00	0	0.03
7	0.01	0.16	0.17	0.01	0	0.09
8	0.02	0.25	0.22	0.01	0	0
9	0.01	0.30	0.15	0.00	0	0.06
10	0.01	0.42	0.16	0.01	0	0.04
TEST	0	0	0	0	0	0
AVG	0.01	0.30	0.17	0.01	0	0.04
MIN	0.01	0.16	0.12	0	0	0
MAX	0.02	0.42	0.22	0.01	0	0.09

Dry Scenario – DP2						
RUN:	R1	R2	R3	R4	R5	R6
1	0.03	0.91	0.26	0.01	0	0.13
2	0.02	0.84	0.22	0.01	0	0.08
3	0.03	0.92	0.26	0.01	0	0.10
4	0.02	0.82	0.22	0.01	0	0.08
5	0.02	0.90	0.26	0.01	0	0.08
6	0.02	0.90	0.26	0.01	0	0.11
7	0.02	0.91	0.27	0.01	0	0.10
8	0.02	0.91	0.22	0.01	0	0.09
9	0.04	0.87	0.25	0.01	0	0.09
10	0.01	0.87	0.27	0.01	0	0.10
TEST	0	0.76	0	0	0	0
AVG	0.02	0.88	0.25	0.01	0	0.10
MIN	0.01	0.82	0.22	0.01	0	0.08
MAX	0.04	0.92	0.27	0.01	0	0.13

Tables S6-S7-S8 Average objective function scores (R1-R6), for each simulation run (1-10). TEST values refer to the test runs on the undisturbed hydrograph; AVG, MIN and MAX values refer to the average, minimum and maximum value for each set, respectively. **Results for the DP2** under dry, normal and wet scenarios.

Normal Scenario – DP2						
RUN:	R1	R2	R3	R4	R5	R6
1	0.01	0.63	0.15	0	0	0.06
2	0.01	0.77	0.20	0.01	0	0.03
3	0.01	0.71	0.24	0.01	0	0.06
4	0.01	0.79	0.20	0.01	0	0.08
5	0.01	0.65	0.16	0	0	0.06
6	0.01	0.75	0.16	0	0	0.05
7	0.02	0.71	0.16	0	0	0.10
8	0.02	0.75	0.24	0.01	0	0.07
9	0.02	0.73	0.18	0	0	0.10
10	0.01	0.72	0.16	0	0	0.06
TEST	0	0	0	0	0	0
AVG	0.01	0.72	0.19	0	0	0.07
MIN	0.01	0.63	0.15	0	0	0.03
MAX	0.02	0.79	0.24	0.01	0	0.10

Wet Scenario – DP2						
RUN:	R1	R2	R3	R4	R5	R6
1	0.02	0.56	0.19	0.01	0	0.06
2	0.02	0.56	0.18	0.02	0	0.10
3	0.02	0.56	0.22	0.01	0	0.09
4	0.02	0.61	0.16	0.01	0	0.07
5	0.01	0.53	0.16	0.02	0	0.03
6	0.01	0.55	0.16	0.02	0	0.08
7	0.02	0.49	0.16	0.02	0	0.05
8	0.01	0.47	0.16	0.01	0	0
9	0.02	0.55	0.18	0.02	0	0.08
10	0.01	0.57	0.14	0.01	0	0.04
TEST	0	0.10	0	0.01	0	0
AVG	0.02	0.54	0.17	0.02	0	0.06
MIN	0.01	0.47	0.14	0.01	0	0.01
MAX	0.02	0.61	0.22	0.02	0	0.10

Table S9. Comparison of average natural discharge values under different scenarios and the optimized discharge thresholds. **Results for DP1** for sub-normal (dry), normal and above-normal (wet) hydrological conditions.

		1-Jan		2-Jan		3-Jan		4-Jan		5-Jan		6-Jan		7-Jan		8-Jan	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	2.2457	2.1846	2.1433	1.8893	2.0454	1.9004	2.0744	1.8983	2.1038	1.9532	2.2377	1.9403	2.3526	2.2639	2.4065	2.2354
	N	2.7257	2.5988	2.8858	2.7747	3.0020	2.9284	3.5120	3.2989	3.3890	2.8362	4.2324	3.4977	4.0577	3.1257	3.6905	2.7677
	W	4.0957	3.6503	3.9504	3.6157	3.8874	3.1336	3.9807	2.8495	4.0785	2.0469	4.4813	2.1496	5.3042	2.8360	5.7497	2.9976

		9-Jan		10-Jan		11-Jan		12-Jan		13-Jan		14-Jan		15-Jan		16-Jan	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	2.5010	2.2804	2.6441	2.4805	2.7434	2.5225	2.7498	2.7045	2.6533	2.5293	2.4970	2.3146	2.3187	2.1072	2.1662	2.0953
	N	3.5470	2.3170	3.3036	2.0606	5.1130	4.1108	5.5450	4.6118	3.6366	2.8122	3.1876	2.2244	3.0762	2.5357	3.0982	2.9497
	W	5.2748	2.3948	5.8818	2.6661	8.3126	5.2834	7.9577	4.8709	8.6646	5.5866	7.4207	4.3734	7.9668	4.9955	7.8124	5.0218

		17-Jan		18-Jan		19-Jan		20-Jan		21-Jan		22-Jan		23-Jan		24-Jan	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	2.0903	1.9933	2.0629	1.7733	2.0046	1.8911	1.9389	1.7969	1.9009	1.7150	1.8231	1.7513	1.7440	1.4668	1.6489	1.5638
	N	3.0693	2.9415	3.0364	2.9618	3.0362	2.9638	3.0741	2.9348	2.9680	2.9399	2.8365	2.6765	2.7691	2.5664	2.7226	2.6797
	W	5.1039	2.1016	4.6233	1.9139	4.4915	2.1019	5.4905	3.1103	5.2642	3.5485	4.1717	3.0730	3.9054	3.1361	3.8537	3.5267

		25-Jan		26-Jan		27-Jan		28-Jan		29-Jan		30-Jan		31-Jan		1-Feb	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	1.5372	1.2378	1.4531	1.3302	1.4448	1.1845	1.8039	1.6777	2.7335	2.6275	2.8264	2.7202	2.7729	2.6280	3.0338	2.9273
	N	2.7416	2.4143	2.7412	2.5030	2.7675	2.6941	3.3228	3.1733	5.5054	5.2479	9.4489	9.4023	7.9027	7.8307	4.8705	4.7677
	W	3.8096	3.6158	3.7796	3.5623	3.7455	3.5272	4.1740	3.9836	6.1210	6.0033	9.7584	9.6226	8.0067	7.8115	4.8312	4.7028

		2-Feb		3-Feb		4-Feb		5-Feb		6-Feb		7-Feb		8-Feb		9-Feb	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	2.3299	2.1615	2.6257	2.5223	5.0380	4.9700	4.8862	4.8125	3.0920	2.7716	2.4365	2.2676	2.3206	2.1576	2.2627	2.1551
	N	5.4828	5.4410	4.2542	4.1289	3.1529	2.9823	3.0167	2.9214	2.7432	2.5975	2.7265	2.6328	2.7367	2.6377	2.7323	2.5280
	W	6.2687	6.2099	5.8129	5.5684	3.7022	3.5933	3.8839	3.6679	4.3662	4.2866	5.3304	4.8475	5.3152	5.1691	4.3391	4.1022

		10-Feb		11-Feb		12-Feb		13-Feb		14-Feb		15-Feb		16-Feb		17-Feb	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	2.1789	1.7532	2.0706	1.9560	1.9471	1.7069	1.8450	1.5966	1.8323	1.5746	1.8646	1.7148	1.8310	1.6593	1.7567	1.4857
	N	2.7748	2.5469	2.8257	2.6675	2.9202	2.7541	2.9483	2.7631	2.9515	2.7310	2.9849	2.8129	2.9948	2.8393	2.9688	2.6983
	W	4.2963	4.1121	4.7142	4.6346	5.3922	5.1212	4.8747	4.4965	4.7773	4.6454	4.6769	4.2442	4.5356	4.0281	4.3590	4.0365

		18-Feb		19-Feb		20-Feb		21-Feb		22-Feb		23-Feb		24-Feb		25-Feb	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	1.6960	1.6174	1.6287	1.4703	1.5475	1.3316	1.4691	1.3115	1.3885	1.3075	1.3384	1.1483	1.2800	1.0989	1.2299	1.0425
	N	2.9843	2.8294	2.9649	2.7627	2.8767	2.6662	2.9847	2.7455	3.6617	3.5198	3.2472	3.0815	3.1388	2.9632	3.0695	2.9018
	W	4.2002	3.8052	4.4525	4.2936	6.8628	6.6463	7.7321	7.5169	7.8569	7.7044	6.6866	6.3663	7.1229	6.9606	8.3145	8.1050

		26-Feb		27-Feb		28-Feb		1-Mar		2-Mar		3-Mar		4-Mar		5-Mar	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	1.2391	0.9494	1.4572	1.2359	1.4838	1.2683	1.9269	1.7973	2.6294	2.4707	1.9782	1.8033	1.8700	1.7712	1.8552	1.7623
	N	3.8954	3.6264	4.5971	4.4568	3.7831	3.6288	3.8788	3.6245	3.9498	3.8355	3.9845	3.7092	4.0828	3.9404	7.7321	7.6262
	W	6.3479	6.2182	5.0231	4.6862	4.0565	3.8330	10.3852	10.2033	4.8606	4.6667	3.7878	3.0214	3.5188	3.1853	3.3865	3.1068

		6-Mar		7-Mar		8-Mar		9-Mar		10-Mar		11-Mar		12-Mar		13-Mar	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	1.8351	1.7110	1.7558	1.5989	1.6461	1.5693	1.5275	1.3506	1.4302	1.2748	1.3468	1.1641	1.2867	1.0584	1.2403	0.8879
	N	9.2405	9.1255	6.2896	6.1797	4.7358	4.5815	4.4838	4.2799	4.5837	4.3900	4.7050	4.4228	4.7584	4.5868	4.7488	4.4044
	W	3.2463	2.7128	3.5411	3.1117	3.2693	2.6859	2.8010	2.3862	2.6518	2.1956	2.5687	1.9402	2.5129	2.0524	2.5511	1.9505

		14-Mar		15-Mar		16-Mar		17-Mar		18-Mar		19-Mar		20-Mar		21-Mar	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	1.2050	1.0028	1.1464	1.0387	1.0929	1.0237	1.0898	0.8689	1.0895	0.8221	1.0589	0.7215	1.0249	0.6807	1.0125	0.6043
	N	4.6397	4.3841	4.4370	4.1468	4.1289	3.8230	3.7565	3.4192	3.3687	2.9568	3.0065	2.6092	2.6932	2.1402	2.4458	2.0502
	W	2.5805	1.8907	2.5928	1.9580	2.6182	2.0729	3.8398	3.0413	4.7201	4.2871	4.7389	4.0422	4.4773	3.9502	3.3369	2.7170

		22-Mar		23-Mar		24-Mar		25-Mar		26-Mar		27-Mar		28-Mar		29-Mar	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	0.9889	0.5625	0.9629	0.5455	0.9328	0.4566	0.9074	0.4478	0.9028	0.3963	0.9168	0.4269	1.0007	0.5031	1.1135	0.6229
	N	2.2428	1.8233	2.1380	1.7384	3.5815	3.2576	4.2546	3.8926	2.6734	2.2019	2.4522	2.1181	2.4809	2.1075	2.5173	2.1171
	W	3.0397	2.4878	2.9286	2.1800	2.9292	2.2443	3.0729	2.5244	5.4967	4.9826	9.8397	9.3603	9.1007	8.6996	5.2282	4.4390

		30-Mar		31-Mar		1-Apr		2-Apr		3-Apr		4-Apr		5-Apr		6-Apr	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	1.1724	0.7060	1.2093	0.7360	1.2300	0.7719	1.2265	0.6805	1.5702	1.1286	2.1318	1.6219	1.7166	1.2112	1.7124	1.2804
	N	3.5561	3.2268	4.2470	3.9301	2.7751	2.3947	2.4750	2.0608	2.7116	2.3252	3.1760	2.8659	5.1577	4.8219	5.0128	4.7083
	W	4.2594	3.7081	5.1398	4.5225	8.5446	8.0997	9.7488	9.3749	7.2017	6.7654	5.1247	4.7419	4.4137	3.8631	4.2165	3.6865

		7-Apr		8-Apr		9-Apr		10-Apr		11-Apr		12-Apr		13-Apr		14-Apr	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	1.7675	1.2464	1.8410	1.1770	1.8819	1.4562	2.3848	1.9202	3.1947	2.7851	2.7022	2.2514	2.7034	2.2691	2.8221	2.3133
	N	2.9113	2.5314	2.4818	2.0884	2.3678	2.0116	2.4019	1.9345	2.5613	2.1556	2.7267	2.3511	2.9369	2.5568	3.0412	2.7156
	W	4.0520	3.4755	4.3254	3.6957	4.5149	4.0304	3.6057	3.1328	3.3386	2.8413	3.2727	2.6069	3.1950	2.6803	3.0212	2.3340

		15-Apr		16-Apr		17-Apr		18-Apr		19-Apr		20-Apr		21-Apr		22-Apr	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	2.9033	2.4362	2.9209	2.3940	2.8773	2.4752	2.8296	2.3929	2.7812	2.3686	3.5949	2.9067	4.5688	4.1575	6.2074	5.8086
	N	3.0388	2.7510	3.0782	2.7277	3.1415	2.8127	3.1201	2.8216	3.0551	2.7266	2.9884	2.6976	2.8780	2.4175	2.7835	2.4980
	W	2.8019	2.3687	2.6040	1.8927	2.4935	1.8581	2.4752	1.9350	2.5067	1.8302	2.5557	2.1054	2.6438	2.0407	2.7200	2.3296

		23-Apr		24-Apr		25-Apr		26-Apr		27-Apr		28-Apr		29-Apr		30-Apr	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	7.6451	7.2982	5.2255	4.7843	2.9874	2.6167	2.7398	2.2348	2.8129	2.4347	2.9078	2.4960	2.9310	2.5315	2.9092	2.4895
	N	2.7315	2.3173	2.6706	2.2964	2.5915	2.1842	2.6099	2.2523	2.6156	2.3667	2.5904	2.3989	2.4957	2.2571	2.4324	2.3611
	W	2.7520	2.1397	2.7340	2.4188	2.6634	2.3160	2.6161	2.2163	2.5629	1.9677	2.5442	2.2191	2.5026	2.0484	2.4360	2.1422

		1-May		2-May		3-May		4-May		5-May		6-May		7-May		8-May	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	2.7138	2.5419	2.6506	2.4860	2.5827	2.4072	2.4783	2.3087	2.3978	2.1972	2.3197	2.0250	2.2808	2.1030	2.3334	2.1707
	N	3.1635	3.0252	3.8837	3.7369	2.9030	2.5071	3.8709	3.7300	5.2409	5.2082	4.0821	3.8715	3.5883	3.4438	4.9160	4.7618
	W	2.3502	1.6832	2.3861	2.1561	2.4353	2.1567	2.4448	2.0616	2.4626	2.1454	2.5133	1.8130	2.5227	2.2136	2.4839	1.9123

		9-May		10-May		11-May		12-May		13-May		14-May		15-May		16-May	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	2.3418	2.1223	2.2832	1.9792	2.1570	1.7666	2.0187	1.7829	1.8594	1.6843	1.6982	1.4351	1.5648	1.2891	1.4832	1.2267
	N	4.3161	4.2624	3.2593	3.0810	3.0110	2.8955	2.9164	2.8392	2.8508	2.6455	2.7193	2.5838	2.5489	2.3472	2.3570	2.2603
	W	2.4126	1.9026	3.3885	3.2422	5.8453	5.7284	6.1771	6.0711	4.3380	4.1463	2.6098	1.9748	2.3287	1.8978	2.2972	1.6976

		17-May		18-May		19-May		20-May		21-May		22-May		23-May		24-May	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	1.3927	0.9566	1.3191	0.9003	1.3008	1.0495	1.3070	0.9848	1.2713	1.0507	1.2141	0.9113	1.1538	0.8534	1.1014	0.9636
	N	2.1797	1.8496	2.0690	1.7609	1.9567	1.8036	1.8237	1.4978	1.6786	1.1971	1.5440	1.3041	1.4298	1.1362	1.3394	1.0341
	W	2.2908	2.0487	2.2990	1.9631	2.3189	1.6315	2.3742	1.8706	2.4060	1.6735	2.3892	2.1036	2.3382	1.9003	4.1688	3.8970

		25-May		26-May		27-May		28-May		29-May		30-May		31-May		1-Jun	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	1.0714	0.8158	1.0457	0.7413	1.0246	0.7308	1.0129	0.6806	1.0026	0.6757	1.0004	0.7398	1.0023	0.7887	0.9749	0.5622
	N	1.2874	1.0722	1.2610	1.0725	1.2297	1.0359	1.1894	0.9172	1.1714	0.6546	1.1813	0.7844	1.1796	0.9189	1.1385	0.6819
	W	4.3294	3.9871	2.7078	2.2649	2.2203	1.7182	2.0798	1.5297	2.0143	1.7625	1.9819	1.7383	1.9774	1.4916	1.8276	1.0757

		2-Jun		3-Jun		4-Jun		5-Jun		6-Jun		7-Jun		8-Jun		9-Jun	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	0.9555	0.4482	0.9787	0.4930	1.0612	0.6661	1.2984	0.9080	1.4285	0.9180	1.4399	0.9956	1.4047	0.8284	1.3422	0.9115
	N	1.1120	0.7188	1.0930	0.5800	1.0865	0.6625	1.1291	0.6970	1.2104	0.7921	1.2379	0.8612	1.2420	0.7744	1.2432	0.8362
	W	1.7801	0.9581	1.7450	1.2042	1.6959	1.0400	1.6270	0.9348	1.5875	1.0028	1.5811	0.8496	1.5838	0.9508	1.5461	1.0199

		10-Jun		11-Jun		12-Jun		13-Jun		14-Jun		15-Jun		16-Jun		17-Jun	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	1.2704	0.8245	1.2014	0.7575	1.1300	0.7056	1.0632	0.6213	1.0049	0.5896	0.9563	0.4287	0.9165	0.4699	0.8843	0.4523
	N	1.2147	0.7853	1.1928	0.7448	1.1969	0.6993	1.1990	0.7652	1.2218	0.6866	1.1947	0.6385	1.1432	0.7190	1.0875	0.5902
	W	1.4841	0.9443	1.3992	0.8695	1.3086	0.6762	1.2228	0.6698	1.1477	0.4675	1.0828	0.5294	1.0275	0.5824	0.9810	0.4136

		18-Jun		19-Jun		20-Jun		21-Jun		22-Jun		23-Jun		24-Jun		25-Jun	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	0.8579	0.4289	0.8360	0.4094	0.8178	0.4157	0.8024	0.3883	0.8103	0.4050	0.8608	0.3507	0.8635	0.3801	0.8425	0.3723
	N	1.0365	0.6455	0.9922	0.5591	0.9549	0.5065	0.9243	0.5373	0.8984	0.4958	0.8767	0.4766	0.8582	0.3899	0.8421	0.4368
	W	0.9428	0.4066	0.9114	0.4112	0.8853	0.3103	0.8874	0.3778	0.9739	0.3843	1.0614	0.5242	1.1024	0.5067	1.0993	0.4862

		26-Jun		27-Jun		28-Jun		29-Jun		30-Jun		1-Jul		2-Jul		3-Jul	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	0.8174	0.3703	0.7939	0.3482	0.7728	0.3700	0.7553	0.3416	0.7397	0.2812	0.7158	0.2555	0.7193	0.3106	0.7443	0.3461
	N	0.8277	0.4214	0.8147	0.3807	0.8021	0.3735	0.7903	0.3296	0.7796	0.3513	0.7621	0.3492	0.7516	0.3064	0.7415	0.3598
	W	1.0706	0.4999	1.0298	0.5324	0.9846	0.4319	0.9393	0.4440	0.8972	0.3854	0.8656	0.2991	0.8443	0.3392	0.8185	0.3230

		4-Jul		5-Jul		6-Jul		7-Jul		8-Jul		9-Jul		10-Jul		11-Jul	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	0.7477	0.2660	0.7377	0.3356	0.7239	0.3544	0.7050	0.3391	0.6864	0.2267	0.6692	0.2556	0.6544	0.2428	0.6414	0.2268
	N	0.7506	0.3579	0.8323	0.3984	0.8597	0.4385	0.8468	0.3958	0.8195	0.4312	0.7887	0.4082	0.7589	0.3187	0.7318	0.2960
	W	0.7924	0.3265	0.7772	0.2655	0.8027	0.3226	0.8062	0.2325	0.7901	0.2712	0.7672	0.2442	0.7525	0.1893	0.7312	0.2401

		12-Jul		13-Jul		14-Jul		15-Jul		16-Jul		17-Jul		18-Jul		19-Jul	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	0.6339	0.2468	0.6275	0.2267	0.6178	0.2049	0.6237	0.2181	0.6357	0.1653	0.6269	0.2025	0.6142	0.2154	0.5990	0.2021
	N	0.7082	0.3159	0.6880	0.2837	0.6702	0.2785	0.6546	0.2392	0.6411	0.2710	0.6282	0.1745	0.6167	0.2258	0.6059	0.2056
	W	0.7076	0.2255	0.6861	0.1705	0.6676	0.1960	0.6513	0.2149	0.6371	0.2076	0.6246	0.1585	0.6131	0.1822	0.6068	0.1500

		20-Jul		21-Jul		22-Jul		23-Jul		24-Jul		25-Jul		26-Jul		27-Jul	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	0.5852	0.2022	0.5722	0.1609	0.5598	0.1164	0.5487	0.1471	0.5387	0.1347	0.5293	0.1361	0.5204	0.1325	0.5121	0.1245
	N	0.5956	0.1855	0.5857	0.1968	0.5762	0.2102	0.5669	0.2053	0.5577	0.1422	0.5488	0.1520	0.5396	0.1844	0.5310	0.1392
	W	0.5974	0.1274	0.5863	0.1153	0.5757	0.1071	0.5660	0.1148	0.5564	0.1047	0.5473	0.1109	0.5384	0.0980	0.5299	0.0936

		28-Jul		29-Jul		30-Jul		31-Jul		1-Aug		2-Aug		3-Aug		4-Aug	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	0.5039	0.1198	0.4962	0.1071	0.4884	0.1001	0.4841	0.1177	0.4821	0.1118	0.4746	0.0827	0.4669	0.0876	0.4596	0.0821
	N	0.5229	0.1359	0.5143	0.1404	0.5057	0.1569	0.4974	0.0949	0.5005	0.1526	1.0747	0.6872	1.8866	1.4559	0.8109	0.3952
	W	0.5213	0.1101	0.5127	0.0856	0.5046	0.0691	0.4963	0.0663	0.4927	0.0743	0.4849	0.0657	0.4768	0.0696	0.4686	0.0523

		5-Aug		6-Aug		7-Aug		8-Aug		9-Aug		10-Aug		11-Aug		12-Aug	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	0.4525	0.0719	0.4451	0.0968	0.4379	0.0773	0.4309	0.0617	0.4240	0.0492	0.4169	0.0476	0.4102	0.0504	0.4030	0.0443
	N	0.5935	0.2016	0.5310	0.1595	0.5087	0.1230	0.4895	0.1053	0.4730	0.0958	0.4587	0.1002	0.4466	0.1017	0.4358	0.0875
	W	0.4608	0.0577	0.4533	0.0377	0.4673	0.0447	0.8703	0.3164	0.5633	0.1019	0.5215	0.0966	0.5029	0.0837	0.4826	0.0570

		13-Aug		14-Aug		15-Aug		16-Aug		17-Aug		18-Aug		19-Aug		20-Aug	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	0.3963	0.0442	0.3898	0.0422	0.3829	0.0291	0.3767	0.0227	0.3699	0.0288	0.3637	0.0189	0.3573	0.0192	0.3510	0.0122
	N	0.4261	0.0886	0.4171	0.0744	0.4089	0.0637	0.4012	0.0623	0.3941	0.0617	0.3869	0.0458	0.3800	0.0439	0.3733	0.0445
	W	0.4612	0.0443	0.4426	0.0350	0.4281	0.0201	0.4351	0.0254	0.4308	0.0256	0.4177	0.0162	0.4041	0.0064	0.3921	0.0026

		21-Aug		22-Aug		23-Aug		24-Aug		25-Aug		26-Aug		27-Aug		28-Aug	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	0.3446	0.0048	0.3386	0.0188	0.3327	0.0033	0.3267	0.0074	0.3305	0.0021	1.3283	0.8197	1.8750	1.2829	1.1745	0.7728
	N	0.3671	0.0394	0.3604	0.0338	0.3544	0.0311	0.3483	0.0283	0.3520	0.0283	0.4023	0.0633	0.4830	0.1044	0.8281	0.4270
	W	0.3962	0.0079	0.4686	0.0522	0.5601	0.1168	0.6569	0.1639	1.9264	1.2972	2.7861	2.1351	1.4190	0.8232	1.1578	0.6941

		29-Aug		30-Aug		31-Aug		1-Sep		2-Sep		3-Sep		4-Sep		5-Sep	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	0.8035	0.3542	0.7064	0.2792	0.6513	0.2786	0.5623	0.4056	0.5126	0.3813	0.4684	0.3703	0.4298	0.3128	0.3984	0.3016
	N	0.6611	0.2444	0.6193	0.2600	0.5837	0.1835	0.5123	0.3934	0.4761	0.3759	0.4415	0.3206	0.4099	0.3188	0.3834	0.2744
	W	1.0368	0.5278	1.0433	0.5791	1.0577	0.4819	0.9793	0.6001	0.9582	0.7917	0.9084	0.6857	0.8430	0.5813	0.7713	0.5568

		6-Sep		7-Sep		8-Sep		9-Sep		10-Sep		11-Sep		12-Sep		13-Sep	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	0.3726	0.3018	0.3519	0.2390	0.3501	0.2547	0.3730	0.2013	0.3755	0.3162	0.3636	0.2285	0.3482	0.1891	0.3330	0.2122
	N	0.3611	0.2517	0.3425	0.2143	0.3423	0.2308	0.3656	0.2375	0.3687	0.2602	0.3572	0.2524	0.3413	0.2577	0.3258	0.2151
	W	0.6992	0.4906	0.6311	0.4725	0.5685	0.4267	0.5134	0.3854	0.4655	0.2878	0.4255	0.2370	0.3923	0.2569	0.3649	0.2763

		14-Sep		15-Sep		16-Sep		17-Sep		18-Sep		19-Sep		20-Sep		21-Sep	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	0.3192	0.2283	0.3077	0.2183	0.2979	0.2184	0.2897	0.1963	0.2829	0.2205	0.2773	0.1495	0.2722	0.1878	0.2677	0.1491
	N	0.3337	0.1839	0.3461	0.2577	0.3335	0.2167	0.3166	0.2093	0.3017	0.1890	0.2902	0.2200	0.2805	0.1943	0.2724	0.1854
	W	0.3433	0.2199	0.3256	0.2298	0.3114	0.2064	0.2997	0.1869	0.2907	0.2107	0.2826	0.2088	0.2755	0.1796	0.2695	0.1567

		22-Sep		23-Sep		24-Sep		25-Sep		26-Sep		27-Sep		28-Sep		29-Sep	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	0.2635	0.1821	0.2597	0.1924	0.2635	0.1674	0.2789	0.1930	0.3035	0.2408	1.6063	1.4372	2.1695	2.0922	0.7746	0.5536
	N	0.2661	0.2090	0.2650	0.2089	0.2964	0.2217	0.3101	0.2193	0.3067	0.2252	0.2969	0.1482	0.2842	0.2170	0.2721	0.2093
	W	0.2651	0.1724	0.2669	0.1764	0.3000	0.2015	0.3436	0.1974	0.3428	0.2487	0.5081	0.4433	1.1800	0.9454	0.4961	0.3734

		30-Sep		1-Oct		2-Oct		3-Oct		4-Oct		5-Oct		6-Oct		7-Oct	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	0.4846	0.2897	0.3971	0.0445	0.4377	0.0652	0.5165	0.1450	0.5448	0.1376	0.5348	0.1460	0.5068	0.1283	0.4716	0.0698
	N	0.2646	0.1610	0.2720	0.0001	0.2721	0.0004	0.2644	0.0007	0.2686	0.0015	0.3026	0.0003	0.3971	0.0623	0.5806	0.1377
	W	0.3535	0.2208	0.3579	0.0002	0.3793	0.0000	0.4228	0.0215	0.5874	0.0956	2.3234	1.6761	3.7977	3.2612	1.9531	1.3115

		8-Oct		9-Oct		10-Oct		11-Oct		12-Oct		13-Oct		14-Oct		15-Oct	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	0.4348	0.0551	0.4047	0.0471	0.3942	0.0443	0.3792	0.0276	0.3721	0.0199	0.3764	0.0325	0.4229	0.0549	0.4411	0.0757
	N	1.5434	0.9987	1.5831	1.0944	1.1376	0.6743	0.9186	0.4433	0.9115	0.4254	0.9280	0.5038	0.9455	0.5089	0.9761	0.5915
	W	1.7685	0.9971	1.8446	1.0608	2.9661	2.2481	3.1294	2.5836	2.0610	1.3319	1.7944	1.0706	1.6950	1.0175	1.6039	0.9959

		16-Oct		17-Oct		18-Oct		19-Oct		20-Oct		21-Oct		22-Oct		23-Oct	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	0.4889	0.0976	0.5042	0.0941	0.5006	0.0945	0.4849	0.0958	0.4996	0.1159	0.5962	0.2042	0.6710	0.2515	0.7016	0.3042
	N	0.9814	0.4913	0.9495	0.5063	0.9099	0.4447	0.9190	0.5148	0.9693	0.4809	0.9617	0.5407	0.9171	0.4181	0.8436	0.3889
	W	1.5068	0.9746	1.4180	0.7353	1.3333	0.7462	1.2319	0.5569	1.1252	0.6041	1.0396	0.4563	1.0217	0.5324	2.0316	1.1784

		24-Oct		25-Oct		26-Oct		27-Oct		28-Oct		29-Oct		30-Oct		31-Oct	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	0.7195	0.2384	0.7298	0.3105	0.6920	0.2294	0.6332	0.2035	0.5827	0.1917	0.5594	0.1618	0.5392	0.7140	0.5666	0.7305
	N	0.7588	0.3015	0.6751	0.2141	0.5983	0.1945	0.5308	0.1342	0.4727	0.0957	0.4275	0.0792	0.3961	0.0643	0.3669	0.0365
	W	2.2700	1.7810	1.4340	0.8435	1.4447	0.8404	1.4794	0.9398	1.5303	1.0255	1.5189	0.8688	1.5096	0.8577	1.7039	0.9911

		1-Nov		2-Nov		3-Nov		4-Nov		5-Nov		6-Nov		7-Nov		8-Nov	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	0.5010	0.6200	0.4858	0.6035	0.4802	0.5781	0.5042	0.6371	0.7672	1.0949	1.8355	3.2900	1.1795	1.7985	1.0716	1.6856
	N	0.3504	0.0226	0.3319	0.0128	0.3377	0.0144	0.3487	0.0251	0.4045	0.0592	0.5173	0.1549	0.5954	0.2154	0.5867	0.1563
	W	1.4049	0.8082	1.3212	0.7780	1.2751	0.6222	1.2341	0.6754	1.1775	0.6271	1.1001	0.5229	1.0175	0.4697	0.9549	0.4530

		9-Nov		10-Nov		11-Nov		12-Nov		13-Nov		14-Nov		15-Nov		16-Nov	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	1.0117	1.6153	0.9776	1.4834	0.9455	1.3862	0.9004	1.3880	0.8631	1.3123	0.9089	1.3645	0.9624	1.4673	0.9827	1.4896
	N	0.5598	0.2125	0.6131	0.2277	2.5040	2.0612	3.5435	3.1766	1.7641	1.3511	1.2925	0.8192	1.4162	0.9785	1.5739	0.9973
	W	0.8923	0.3443	0.8829	0.3579	0.8986	0.3833	1.0812	0.5613	1.5186	0.8635	1.3422	0.8434	1.5399	0.7805	1.7742	1.0544

		17-Nov		18-Nov		19-Nov		20-Nov		21-Nov		22-Nov		23-Nov		24-Nov	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	1.0544	1.5747	1.1080	1.6839	1.1777	1.9183	1.2991	2.1219	1.3658	2.2453	1.3505	2.2080	1.3161	2.2512	1.2843	2.0735
	N	1.7424	1.1776	1.9090	1.4432	3.1199	2.7685	7.9024	7.5619	8.8303	8.5053	5.0315	4.6232	2.6426	2.1757	2.2236	1.7224
	W	1.9993	1.3698	2.2624	1.4535	2.4597	1.8570	2.5680	2.0320	2.5981	2.0194	2.7191	2.1158	4.3265	3.8109	6.9175	6.4368

		25-Nov		26-Nov		27-Nov		28-Nov		29-Nov		30-Nov		1-Dec		2-Dec	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	1.2465	2.0273	1.2487	2.1048	1.8713	3.3058	2.3864	4.2503	1.8804	3.3413	2.0066	3.5843	3.1376	5.7084	4.5510	7.3650
	N	2.1925	1.7451	2.2642	1.8979	2.3868	1.8331	2.3918	1.9936	3.0699	2.4276	4.2200	3.8812	3.3481	2.3358	3.5534	2.1921
	W	7.6423	7.1100	6.9757	6.5327	6.0843	5.5846	5.0748	4.3856	3.3812	2.8116	4.2726	3.7749	4.9556	4.9014	3.5778	3.4179

		3-Dec		4-Dec		5-Dec		6-Dec		7-Dec		8-Dec		9-Dec		10-Dec	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	4.4096	6.0189	4.4953	6.2822	4.4979	6.3071	4.5202	6.9455	3.8592	6.1173	2.5728	5.0002	2.2521	4.3433	4.4108	8.6605
	N	4.2340	2.5455	4.5928	2.8806	4.7306	2.9894	4.8364	3.1349	4.2284	2.7836	2.9655	2.1691	2.6561	2.5180	2.6057	2.3816
	W	2.9753	2.6393	2.7657	2.5760	5.8692	5.7241	6.3517	6.1400	5.4423	5.2090	5.5900	5.5053	3.4395	3.2209	2.7279	1.9984

		11-Dec		12-Dec		13-Dec		14-Dec		15-Dec		16-Dec		17-Dec		18-Dec	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	5.1012	10.1340	2.9426	5.7675	2.7115	5.2729	2.4732	4.8381	2.4429	4.7426	2.3722	4.5852	2.2684	4.3611	2.0961	3.9632
	N	2.5689	2.5145	2.4932	2.3309	2.3550	2.1929	2.2351	1.9389	2.1910	2.1141	2.3155	2.0749	2.4488	2.3727	2.1038	1.9965
	W	2.7078	2.4504	2.8734	2.3941	3.8099	3.4698	4.7146	4.4621	3.5100	3.2225	3.2944	3.0038	3.9007	3.5878	6.8284	6.6278

		19-Dec		20-Dec		21-Dec		22-Dec		23-Dec		24-Dec		25-Dec		26-Dec	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	1.9058	3.6603	1.7288	3.2229	1.5924	2.9595	1.5626	3.0176	1.5185	2.7345	1.4438	2.7891	3.8113	7.3707	5.2902	10.4833
	N	2.0589	1.9343	2.1124	2.0093	2.1683	1.9860	2.2501	2.0714	2.3328	2.0686	2.3309	2.2156	2.2330	1.9799	2.1550	1.9894
	W	6.8255	6.6454	4.0592	3.9888	3.6380	3.4711	6.1654	6.0966	8.2585	7.9432	6.0289	5.9600	4.3602	4.0142	3.9467	3.8059

		27-Dec		28-Dec		29-Dec		30-Dec		31-Dec	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	3.1512	6.2538	2.0577	3.9408	1.9317	3.5916	1.9722	3.7903	2.0461	4.0311
	N	2.2859	2.1686	2.4646	2.1413	2.5584	2.4971	2.5864	2.5366	2.6374	2.5547
	W	3.7929	3.6296	3.9079	3.7087	3.9912	3.7950	3.9782	3.7834	3.8760	3.6872

Table S10. Comparison of average natural discharge values under different scenarios and the optimized discharge thresholds. **Results for DP2** for sub-normal (dry), normal and above-normal (wet) hydrological conditions.

		1-Jan		2-Jan		3-Jan		4-Jan		5-Jan		6-Jan		7-Jan		8-Jan	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
	D	5.9146	5.1633	5.8658	5.8016	5.8241	5.3982	8.0919	7.9802	11.6450	9.9287	11.7683	8.1527	10.0950	6.3245	8.4880	4.9904
S	N	11.1707	6.7491	14.4555	9.0357	15.2655	9.3264	11.9407	5.0480	10.3348	3.4738	9.7044	2.8087	9.3389	4.6792	8.9967	6.3579
	W	7.1581	6.7271	6.8927	6.0190	6.5863	6.0478	6.6051	6.3284	6.6644	6.3814	10.1940	9.0921	12.3759	12.1318	9.3709	8.8301

		9-Jan		10-Jan		11-Jan		12-Jan		13-Jan		14-Jan		15-Jan		16-Jan	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
	D	8.9824	7.8267	8.2789	7.9379	11.0679	10.8602	12.3161	12.0747	9.0844	8.9502	8.1350	8.0069	7.6004	7.3940	7.1883	6.9447
S	N	8.7574	7.8383	8.7861	8.4910	8.9725	8.8030	9.1509	8.8580	9.1956	8.3604	10.6037	10.2016	11.7701	11.6364	9.8958	9.6746
	W	7.5974	6.6675	6.7264	5.7368	8.7881	8.4770	10.8640	10.3762	11.3025	10.3580	8.8636	8.4528	14.3422	13.8453	17.2921	16.8148

		17-Jan		18-Jan		19-Jan		20-Jan		21-Jan		22-Jan		23-Jan		24-Jan	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
	D	6.9008	6.7387	6.6818	6.2228	6.3965	6.2099	6.0787	5.7220	5.7248	5.2345	5.3054	5.0008	5.0197	4.5028	4.9104	4.7042
S	N	10.5951	10.2670	9.1007	8.3591	8.9189	8.2136	8.8316	7.7451	8.5485	7.6466	8.2429	7.3491	8.1096	7.6890	8.0001	7.8154
	W	10.1931	9.3158	8.0715	7.2717	7.5939	7.0546	10.4792	9.9329	11.9981	11.6958	8.9785	8.4436	8.1560	7.4967	8.0277	7.2152

		25-Jan		26-Jan		27-Jan		28-Jan		29-Jan		30-Jan		31-Jan		1-Feb	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
	D	4.6973	4.1178	4.5876	4.3929	4.7392	4.0213	7.3309	7.1011	10.1129	9.9979	10.8676	10.6711	11.4307	10.8745	8.4899	8.1633
S	N	7.8016	7.5366	7.6508	7.1563	7.5163	7.3217	8.1773	7.9765	9.5691	9.2567	7.9927	7.5399	7.4508	7.1080	6.8833	6.2222
	W	8.1609	7.3929	8.7973	8.2303	9.9886	9.5668	9.1053	8.7601	9.2133	8.6721	17.5653	17.2366	22.6549	22.4590	20.9461	20.3483

		2-Feb		3-Feb		4-Feb		5-Feb		6-Feb		7-Feb		8-Feb		9-Feb	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
	D	6.8656	6.7282	6.8099	6.6133	9.2807	9.0205	9.8594	9.6123	7.6835	7.5104	5.4631	4.9135	4.8250	4.1981	4.6088	4.0372
S	N	6.5604	5.8804	6.2866	5.3730	6.1985	5.5013	6.0779	5.6686	6.0441	5.4715	6.1002	5.8084	6.2115	5.8520	6.2336	5.7592
	W	19.2496	18.4912	13.5318	13.2899	8.7213	8.0281	16.1002	15.8882	17.5735	17.2156	12.3853	11.8613	14.9532	14.7334	17.7952	17.4511

		10-Feb		11-Feb		12-Feb		13-Feb		14-Feb		15-Feb		16-Feb		17-Feb	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
	D	4.5035	4.1415	4.3850	4.2995	4.2053	3.6044	4.0300	3.5686	3.9246	3.2353	3.7809	3.7293	3.5910	3.0604	3.4488	2.9547
S	N	7.1114	6.4764	8.3860	7.9498	7.1648	6.2263	6.8076	6.4940	7.8186	7.0299	9.7197	9.4681	8.1948	7.3534	7.8098	7.4871
	W	15.4372	15.0466	12.9516	12.3782	11.3973	10.8741	9.5173	8.6465	9.0457	8.0864	8.6752	7.8724	8.2531	7.6846	7.8213	7.3213

		18-Feb		19-Feb		20-Feb		21-Feb		22-Feb		23-Feb		24-Feb		25-Feb	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
	D	3.4480	3.1434	3.3754	2.7030	3.2275	2.8098	3.0539	2.3635	3.0106	2.5984	3.0654	2.5849	3.0950	2.7817	3.1562	2.5871
S	N	7.8037	7.4799	7.8720	7.3843	11.9543	11.4844	15.7759	15.3238	12.8725	12.4596	9.8458	8.6732	8.1697	7.8545	7.8028	7.3936
	W	7.4962	6.2218	7.2444	6.2278	8.3657	7.9573	9.2730	8.4120	8.7926	7.9836	10.3963	9.6157	14.7863	14.4472	13.0764	12.3687

		26-Feb		27-Feb		28-Feb		1-Mar		2-Mar		3-Mar		4-Mar		5-Mar	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
	D	3.7836	3.4432	5.1123	4.3975	4.5989	4.1939	4.9216	4.6839	5.3576	5.1038	5.6116	5.2736	6.5544	6.4718	8.8148	8.5601
S	N	7.8012	7.3909	7.9878	7.0528	10.4509	10.0862	11.9198	11.6490	10.5412	10.0278	10.9771	10.3815	12.5552	12.2145	13.8471	13.5940
	W	12.2777	11.5278	11.5055	10.5656	9.1705	8.3098	8.1396	7.3829	7.8039	6.8696	7.6944	7.1989	7.5093	6.9778	7.1982	6.4696

		6-Mar		7-Mar		8-Mar		9-Mar		10-Mar		11-Mar		12-Mar		13-Mar	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	8.5864	8.3199	6.4772	5.9525	5.5845	4.6865	5.1615	4.9457	4.8999	4.3689	4.6734	4.4299	4.5104	3.8878	4.3855	4.0373
	N	17.1226	16.8061	11.8383	11.4084	10.4361	9.9781	9.8414	9.2835	9.4635	9.0134	9.0982	8.4216	8.6483	8.2479	8.2029	7.5302
	W	6.8094	5.1821	6.4120	5.4655	6.1372	5.2980	5.9552	4.5650	5.9586	5.4829	6.0216	4.9650	6.1866	5.2086	6.4799	5.5402

		14-Mar		15-Mar		16-Mar		17-Mar		18-Mar		19-Mar		20-Mar		21-Mar	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	4.2565	3.9005	4.0762	3.6728	3.9447	3.1724	4.0796	3.5735	4.2603	3.3998	5.2744	4.2768	6.5547	5.6764	5.6139	4.3377
	N	7.7115	7.1958	7.2754	6.4271	6.8455	6.1373	6.4829	5.7376	6.1834	5.0151	6.8297	5.7280	7.8390	6.8405	6.6535	5.6038
	W	6.8306	5.6089	6.9802	6.0654	7.0563	5.7148	7.1815	5.4488	7.0834	5.4957	6.8087	5.1562	6.4699	4.6151	6.1759	4.5104

		22-Mar		23-Mar		24-Mar		25-Mar		26-Mar		27-Mar		28-Mar		29-Mar	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	4.5790	3.4303	4.2768	3.1932	4.1283	2.7169	4.0052	2.7265	3.8982	2.8197	3.9584	2.7329	5.3337	4.2362	6.3549	5.1690
	N	5.5910	4.0920	5.6560	4.5400	12.0547	10.9851	14.9598	13.9552	8.5633	7.2949	7.3997	6.3561	7.3082	5.8948	7.5194	6.5644
	W	5.9103	4.0643	5.8599	4.3993	12.2058	10.6308	15.2464	13.7401	9.8862	8.3515	11.0741	9.0614	12.6458	11.2812	10.7939	8.7317

		30-Mar		31-Mar		1-Apr		2-Apr		3-Apr		4-Apr		5-Apr		6-Apr	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	5.3252	4.0268	5.1824	3.8890	5.1483	3.7045	5.0046	3.6775	10.1444	8.9890	12.7100	11.5487	6.8188	5.7047	5.4791	3.9489
	N	7.7324	6.5971	7.8958	6.4195	7.6946	6.6637	7.4983	6.5540	7.3111	6.4937	7.6244	6.7226	13.9029	13.0314	15.2637	14.3860
	W	12.3276	10.6292	12.9332	11.2585	13.7515	12.2431	17.3913	15.9856	14.9555	13.4831	10.3469	8.7366	8.6734	7.2409	8.3200	6.8539

		7-Apr		8-Apr		9-Apr		10-Apr		11-Apr		12-Apr		13-Apr		14-Apr	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	5.2005	3.8899	5.1213	4.0583	5.0586	3.6675	6.9466	5.7742	8.8957	7.6801	6.6243	5.4591	5.8371	4.6557	5.8437	4.7285
	N	8.4938	7.3629	6.7886	5.5873	7.1917	6.2523	8.7546	7.6861	7.5038	6.4876	7.4705	6.1821	7.9810	6.9659	8.5179	7.5668
	W	8.2358	6.5014	8.7917	7.0663	9.6592	7.8611	8.1310	6.2366	7.7902	5.7418	7.7870	6.4488	7.9391	6.0767	7.9975	5.8931

		15-Apr		16-Apr		17-Apr		18-Apr		19-Apr		20-Apr		21-Apr		22-Apr	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	6.0217	4.7900	6.1592	4.9091	6.2263	5.0510	6.1975	5.0741	6.0347	4.6672	10.8383	9.7861	14.1574	13.1609	15.7554	14.7685
	N	8.8553	8.0381	9.0656	7.5580	9.1081	8.2979	8.9783	7.9460	8.7938	7.9447	8.5956	7.5281	8.3941	7.6058	8.2986	7.0604
	W	7.8833	6.1861	7.6890	5.8771	7.5705	6.0096	7.7101	5.8845	7.8908	5.8875	8.0227	6.0726	8.1542	6.6081	8.1841	6.6429

		23-Apr		24-Apr		25-Apr		26-Apr		27-Apr		28-Apr		29-Apr		30-Apr	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	17.7058	16.7750	13.3488	12.3881	9.8111	8.9239	8.7121	7.8760	7.3318	6.6529	8.0333	7.3522	7.1511	6.2447	6.8859	6.0621
	N	8.1611	7.2953	7.9052	6.6133	7.6453	6.3234	7.4739	6.1458	7.1905	6.4652	6.7995	5.7268	6.4177	5.4023	6.1184	5.0940
	W	8.0410	6.6781	7.7836	5.6901	7.8137	6.4130	8.9584	7.7681	7.9468	6.7389	7.7298	6.3123	7.7552	5.9696	7.8824	6.9869

		1-May		2-May		3-May		4-May		5-May		6-May		7-May		8-May	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	6.4244	6.1201	6.2095	5.6812	5.8676	5.6303	5.4689	4.9159	5.1952	4.6827	5.2268	4.4804	6.2950	6.1197	7.5646	7.0481
	N	7.0488	6.3545	8.4384	8.2554	6.1000	5.8327	7.3336	6.6260	12.3509	12.1350	11.1608	11.0245	10.0151	9.7028	13.3469	13.1240
	W	9.7913	8.9231	14.8507	14.2464	14.9078	14.4416	14.2000	14.0951	16.7144	16.5044	13.9847	13.7960	12.1086	11.7335	13.1152	12.9151

		9-May		10-May		11-May		12-May		13-May		14-May		15-May		16-May	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	5.9789	5.7231	9.6424	9.5245	13.0555	12.9337	11.7906	11.7157	9.4617	9.0890	5.9519	5.6684	5.0001	4.4944	4.6890	4.0250
	N	13.0348	12.8200	12.4283	11.8218	15.1126	14.9642	14.3281	14.1324	12.4094	12.1097	8.2627	7.0518	7.3048	6.9205	7.0646	6.6622
	W	10.6102	9.8567	8.1731	7.3364	7.4299	6.3583	7.7709	7.2887	7.9114	7.3612	6.9713	6.0879	6.7397	5.7884	6.5895	6.0202

		17-May		18-May		19-May		20-May		21-May		22-May		23-May		24-May	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	4.6842	4.2811	4.8680	4.2299	4.6836	4.2398	4.6400	3.9325	4.5322	3.8337	4.3725	3.8258	4.1514	3.6580	3.9079	3.5854
	N	7.1129	6.8922	7.3316	6.9291	7.0418	6.4214	6.7568	6.1000	6.4211	5.6896	6.0409	5.4981	5.6393	5.1248	5.2253	4.7084
	W	6.3784	5.9962	6.0998	4.6354	7.4694	6.8675	9.0098	8.5039	6.1314	5.1889	5.3087	4.4848	4.9284	3.9976	9.5318	8.8629

		25-May		26-May		27-May		28-May		29-May		30-May		31-May		1-Jun	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	3.6902	3.0581	3.5172	2.9724	3.4828	3.0123	3.5260	2.6913	3.4655	2.6083	3.4180	2.4118	3.4156	3.0697	3.4484	2.2524
	N	4.8861	4.1581	4.5452	3.5361	4.2268	3.6242	3.8928	2.9735	3.5793	2.4379	3.3399	2.7041	3.1135	2.3958	2.9372	1.8920
	W	12.1865	11.4899	7.3804	6.3897	4.9409	3.9684	4.2585	2.9157	4.0551	2.9437	4.1308	3.3421	4.2041	3.2120	4.1204	2.4090

		2-Jun		3-Jun		4-Jun		5-Jun		6-Jun		7-Jun		8-Jun		9-Jun	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	3.4800	2.1155	3.5952	2.3733	3.7703	2.4896	4.1821	2.9407	4.3758	3.1174	4.2881	2.9983	4.0889	2.8487	3.8261	2.7831
	N	2.8075	1.7075	2.7409	1.3328	2.6757	1.3124	2.7528	1.7400	2.9401	1.6693	3.0405	1.8480	3.1155	1.6577	3.1359	1.7055
	W	4.0044	2.3777	3.8554	2.1549	3.8292	2.0298	3.9477	2.3039	4.0790	2.4548	4.1741	2.6887	4.3431	2.5066	4.4125	2.8613

		10-Jun		11-Jun		12-Jun		13-Jun		14-Jun		15-Jun		16-Jun		17-Jun	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	3.6138	2.2481	3.5080	2.4204	3.3179	2.1222	3.0836	1.9186	2.9190	1.7955	2.7490	1.5626	2.5728	1.3991	2.4411	1.2127
	N	3.0616	1.7574	2.9328	1.8695	2.7835	1.4517	2.6332	1.2372	2.5159	1.3677	2.5247	1.4584	2.5095	1.3153	2.4507	1.2332
	W	4.4035	2.5182	4.3377	2.7233	4.2673	2.7453	4.0965	2.4414	3.9731	2.0430	3.7865	2.0126	3.5711	1.7456	3.3354	1.5510

		18-Jun		19-Jun		20-Jun		21-Jun		22-Jun		23-Jun		24-Jun		25-Jun	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	2.3449	1.0250	2.2678	1.1944	2.2293	1.0381	2.1730	0.9874	2.1482	0.8879	2.1831	1.1021	2.1393	1.0597	2.0576	0.7790
	N	2.4474	1.3794	2.4024	1.3678	2.5742	1.4411	3.4546	2.2365	2.6913	1.4838	2.4252	1.2683	2.3790	1.2935	2.3356	1.1165
	W	3.0952	1.4886	2.8781	1.1440	2.7659	1.2533	5.0593	3.7061	10.4695	9.0091	9.4238	8.0353	5.6661	3.9214	3.6694	1.7337

		26-Jun		27-Jun		28-Jun		29-Jun		30-Jun		1-Jul		2-Jul		3-Jul	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	1.9761	0.8550	1.9600	0.6438	1.9864	0.8002	2.0888	0.8909	2.1206	0.8064	2.0721	0.8746	2.2631	1.1344	2.4663	1.4647
	N	2.2649	1.0827	2.1702	1.0538	2.0726	0.9011	1.9929	0.9982	1.9641	0.8283	2.0326	0.9179	2.0276	1.0315	2.0064	0.7721
	W	3.2107	1.7351	3.1207	1.2491	3.0628	1.4453	2.9542	1.5014	2.8148	1.2192	2.7863	1.3714	2.7201	1.3191	2.6770	1.0216

		4-Jul		5-Jul		6-Jul		7-Jul		8-Jul		9-Jul		10-Jul		11-Jul	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	2.5841	1.2173	2.7360	1.4799	2.8308	1.8191	2.7985	1.5064	2.6842	1.4747	2.5308	1.3647	2.4426	1.2294	2.5570	1.2607
	N	2.1015	0.8322	2.9099	1.8326	2.6012	1.4424	2.6292	1.4291	2.6762	1.2592	2.6354	1.6551	2.5394	1.1901	2.4362	1.1849
	W	2.5836	0.9722	2.5489	0.9360	2.6547	0.9730	2.8442	1.3590	3.0911	1.2808	3.1771	1.5818	3.2197	1.6556	3.1577	1.1913

		12-Jul		13-Jul		14-Jul		15-Jul		16-Jul		17-Jul		18-Jul		19-Jul	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	2.5411	1.3788	2.4149	1.2422	2.2672	1.2680	2.2882	1.0140	2.8442	1.5298	4.0138	2.6622	2.9008	1.6371	2.6293	1.3576
	N	2.2927	1.0867	2.1370	0.8955	1.9899	0.9112	1.8585	0.6819	1.7445	0.5795	1.6468	0.5953	1.5645	0.5223	1.5016	0.4833
	W	3.0057	1.6364	2.8135	1.2734	2.6140	1.1469	2.4226	0.9136	2.2471	0.7356	2.0911	0.6730	1.9683	0.5854	1.8758	0.4367

		20-Jul		21-Jul		22-Jul		23-Jul		24-Jul		25-Jul		26-Jul		27-Jul	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	2.5121	1.3944	2.3649	1.3486	2.1981	1.0016	2.0356	0.9168	1.8908	0.5690	1.7669	0.5885	1.6646	0.5476	1.5802	0.5150
	N	1.5252	0.5108	1.5284	0.4726	1.4940	0.4691	1.4457	0.4599	1.3997	0.4366	1.3553	0.4428	1.3141	0.2612	1.3155	0.3619
	W	1.7803	0.4321	1.6930	0.3643	1.6342	0.2609	1.5806	0.2623	1.5266	0.2456	1.4767	0.1707	1.4324	0.2028	1.3946	0.1518

		28-Jul		29-Jul		30-Jul		31-Jul		1-Aug		2-Aug		3-Aug		4-Aug	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	1.5117	0.4798	1.4558	0.3264	1.4097	0.3376	1.3713	0.3028	1.3788	0.3191	1.3491	0.2881	1.3229	0.2891	1.3297	0.2558
	N	1.3033	0.3150	1.2767	0.2953	1.2596	0.3063	1.2304	0.2909	1.2145	0.2713	1.7020	0.6097	2.9712	1.5183	2.0623	1.0605
	W	1.3989	0.1550	1.3835	0.1691	1.3486	0.1341	1.3130	0.0979	1.3095	0.0828	1.2787	0.0531	1.2620	0.0546	1.2408	0.0309

		5-Aug		6-Aug		7-Aug		8-Aug		9-Aug		10-Aug		11-Aug		12-Aug	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	1.3883	0.2808	1.4116	0.3568	1.4286	0.3996	1.3965	0.3509	1.3471	0.2989	1.2993	0.1974	1.2576	0.1855	1.2207	0.2405
	N	1.9490	0.7974	1.9227	0.7196	1.9091	0.7914	1.8306	0.6511	1.7270	0.6933	1.7017	0.5625	1.6379	0.5742	1.5459	0.5352
	W	1.2147	0.0247	1.1897	0.0115	1.1899	0.0050	1.2581	0.0507	1.2962	0.0774	1.3164	0.0982	1.2902	0.0517	1.2393	0.0364

		13-Aug		14-Aug		15-Aug		16-Aug		17-Aug		18-Aug		19-Aug		20-Aug	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	1.1895	0.2084	1.1617	0.1634	1.1368	0.1294	1.1143	0.1265	1.0931	0.1122	1.0732	0.0823	1.0544	0.0946	1.0358	0.0558
	N	1.4532	0.4604	1.3506	0.3193	1.2541	0.2767	1.1709	0.1992	1.1025	0.1271	1.0467	0.1412	1.0013	0.0879	0.9639	0.0551
	W	1.1871	0.0138	1.1409	0.0076	1.1039	0.0136	1.1142	0.0128	1.1051	0.0057	1.0746	0.0050	1.0411	0.0091	1.0104	0.0100

		21-Aug		22-Aug		23-Aug		24-Aug		25-Aug		26-Aug		27-Aug		28-Aug	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	1.0180	0.0598	1.0005	0.0354	0.9832	0.0250	0.9664	0.0202	0.9545	0.0087	1.6778	0.4990	2.9627	1.6082	1.8227	0.6715
	N	0.9330	0.0387	0.9071	0.0205	0.8845	0.0130	0.8644	0.0024	0.8465	0.0007	0.8298	0.0030	2.2559	0.8518	3.6919	2.4160
	W	1.4241	0.1638	3.1455	1.5704	3.0259	1.1505	4.0745	2.3095	11.3647	9.5451	26.9707	25.7634	32.8884	31.6406	17.6805	16.3611

		29-Aug		30-Aug		31-Aug		1-Sep		2-Sep		3-Sep		4-Sep		5-Sep	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	1.52945	0.3901043	1.3858	0.2865	1.2830	0.2865	1.1551	0.9576	1.1356	0.6538	1.0958	0.7947	1.0393	0.8279	0.9842	0.6840
	N	1.849235	0.64480258	1.4079	0.3838	1.2491	0.3025	1.1095	0.8053	1.0397	0.7965	0.9731	0.6915	0.9127	0.6279	0.8607	0.5660
	W	5.864919	4.10378229	3.1877	1.7329	2.6695	1.1631	2.3503	1.9257	2.3040	1.7896	2.1960	1.5901	2.0497	1.5053	1.8879	1.7056

		6-Sep		7-Sep		8-Sep		9-Sep		10-Sep		11-Sep		12-Sep		13-Sep	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	0.9368	0.7161	0.8966	0.6224	0.8640	0.6068	0.8364	0.5433	0.8131	0.5549	0.7934	0.5842	0.7758	0.4810	0.7602	0.5578
	N	0.8162	0.5078	0.7794	0.5489	0.7838	0.4956	0.8525	0.5521	0.8696	0.6514	0.8485	0.5897	0.8134	0.6067	0.7741	0.4934
	W	1.7254	1.2292	1.5706	1.1299	1.4280	0.9838	1.3011	0.7195	1.1902	0.6605	1.0952	0.8452	1.0151	0.5393	0.9808	0.6307

		14-Sep		15-Sep		16-Sep		17-Sep		18-Sep		19-Sep		20-Sep		21-Sep	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	0.7455	0.4709	0.7320	0.4538	0.7188	0.4303	0.7065	0.5100	0.6940	0.4278	0.6826	0.4147	0.6917	0.4256	0.7398	0.5500
	N	0.7378	0.5235	0.7063	0.4864	0.7115	0.4555	0.7792	0.3338	0.8229	0.6472	0.7974	0.5185	0.8106	0.5371	0.9826	0.6980
	W	1.1248	0.8614	1.2496	0.7964	1.2572	0.8864	1.2330	0.7046	1.1916	0.8596	1.1586	0.7754	1.1578	0.7787	1.1730	0.7818

		22-Sep		23-Sep		24-Sep		25-Sep		26-Sep		27-Sep		28-Sep		29-Sep	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	0.7554	0.5581	0.8421	0.5358	0.9404	0.6220	1.0365	0.6874	1.1944	0.9658	1.3052	0.8581	1.3674	1.0723	1.3562	1.0849
	N	1.1017	0.7723	1.1102	0.6635	1.1255	0.8698	1.1015	0.6695	1.0936	0.6342	10.7247	10.0813	17.5891	17.3877	9.8326	9.6637
	W	1.3118	1.0718	1.5769	1.2108	1.9805	1.2219	2.2870	1.3359	2.4354	1.8032	6.4889	5.9912	8.5096	7.9388	4.9894	4.2672

		30-Sep		1-Oct		2-Oct		3-Oct		4-Oct		5-Oct		6-Oct		7-Oct	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	1.2969	0.9542	1.1773	0.1700	1.2374	0.2163	1.3863	0.3214	1.5022	0.4635	1.5845	0.5207	1.5918	0.4458	1.5099	0.3789
	N	6.2029	5.6377	2.9015	1.7289	2.2535	0.8818	2.1350	0.9233	2.1156	1.0217	2.1014	1.0320	2.1161	0.9128	2.0443	1.0367
	W	5.7725	5.3002	3.6169	1.8947	3.1421	1.5520	3.1242	1.6004	7.6494	6.1489	25.4186	24.1455	30.2901	28.9340	20.2852	18.9737

		8-Oct		9-Oct		10-Oct		11-Oct		12-Oct		13-Oct		14-Oct		15-Oct	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	1.4399	0.3282	1.3532	0.3299	1.2881	0.2631	1.2656	0.2316	1.2076	0.2071	1.8389	0.6029	3.0687	1.7698	1.9005	0.8051
	N	1.9072	0.6985	1.8051	0.6016	1.7745	0.6880	1.6892	0.4974	1.5765	0.5370	1.5210	0.4659	1.5920	0.4686	1.6083	0.4765
	W	16.3206	14.8188	14.7483	13.3618	14.3347	12.9802	12.4702	11.1529	9.1980	7.4608	7.9880	6.2630	7.6522	5.6240	7.4519	6.0296

		16-Oct		17-Oct		18-Oct		19-Oct		20-Oct		21-Oct		22-Oct		23-Oct	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	1.7236	0.5720	1.7253	0.4519	1.7144	0.6342	1.6830	0.4644	2.0260	0.7577	3.3395	2.2814	2.3925	1.1296	2.3433	1.3143
	N	1.6492	0.5773	1.6809	0.4799	1.6781	0.5851	1.7291	0.5318	1.8553	0.7855	1.9362	0.8112	1.9646	0.8525	1.9078	0.6215
	W	7.4072	5.6920	7.4482	5.7782	7.3653	5.5991	7.4474	4.8515	7.4316	5.7609	7.3134	5.7374	8.4531	6.7027	13.4410	12.0682

		24-Oct		25-Oct		26-Oct		27-Oct		28-Oct		29-Oct		30-Oct		31-Oct	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	2.5711	1.4334	2.6796	1.5318	2.6292	1.3578	2.5363	1.4659	2.6110	1.4194	2.6551	1.6187	2.6638	1.5686	2.7915	1.6076
	N	1.7890	0.6003	1.6431	0.5686	1.5113	0.3991	1.3855	0.3480	1.3430	0.3518	1.2682	0.2575	1.1648	0.2096	1.0947	0.1674
	W	11.8480	10.4146	8.7991	7.2913	9.1711	7.6015	6.9885	5.2715	6.2949	4.7133	5.9132	4.3694	8.0965	6.0660	9.0093	7.4512

		1-Nov		2-Nov		3-Nov		4-Nov		5-Nov		6-Nov		7-Nov		8-Nov	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	2.9771	1.6847	3.0125	1.5303	3.1773	2.0319	3.2931	2.1834	3.5885	2.5129	6.1260	4.8771	6.3180	5.1842	5.0973	3.6703
	N	1.1943	0.1961	1.3106	0.3286	1.3727	0.4079	1.5797	0.4469	2.1670	1.0331	2.7304	1.5004	4.3701	2.8853	3.2863	2.1982
	W	5.7257	3.1375	4.7647	2.4272	4.4774	2.7557	4.4685	3.0406	4.5189	2.9150	4.4916	2.7266	4.2842	2.5924	3.9757	2.2810

		9-Nov		10-Nov		11-Nov		12-Nov		13-Nov		14-Nov		15-Nov		16-Nov	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	4.8060	3.5922	4.6694	3.5772	4.5538	3.1026	4.4774	2.9603	6.4936	5.2165	8.1117	7.1117	5.2935	4.3082	4.5837	3.3500
	N	3.1422	1.9422	11.5229	10.5560	19.0863	18.0476	11.7063	10.6288	6.8339	5.4557	5.9757	4.8146	6.1514	4.5122	6.5231	5.4916
	W	3.6798	2.1422	3.5327	1.4782	3.4449	1.7786	5.5205	3.6550	7.5281	6.0633	5.2497	3.7623	5.3719	3.7031	5.9470	4.1866

		17-Nov		18-Nov		19-Nov		20-Nov		21-Nov		22-Nov		23-Nov		24-Nov	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	4.6373	3.4983	4.7711	3.5476	4.9577	3.7909	5.1780	4.1034	5.4225	4.1860	5.7324	4.4107	6.1215	5.0690	6.4319	5.4832
	N	6.8663	5.9431	7.1498	6.2140	9.7985	8.8578	20.4104	19.3965	21.9968	21.1020	13.1975	12.2078	8.4870	7.2448	10.9112	9.8408
	W	8.4686	6.9315	10.7413	9.2208	10.8529	9.5326	18.3932	17.0213	17.4201	16.0844	11.8470	10.4315	10.3684	8.8995	8.6730	7.2564

		25-Nov		26-Nov		27-Nov		28-Nov		29-Nov		30-Nov		1-Dec		2-Dec	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	6.4513	5.5015	6.4030	5.0514	9.1374	8.1889	9.1685	8.2012	7.0362	5.9620	8.5219	7.4617	11.8651	11.7668	10.0751	9.8741
	N	18.4944	17.4275	25.0210	24.0459	19.0425	18.0886	14.4285	13.5063	11.0000	9.9628	7.6894	6.2212	6.7946	6.4621	11.4421	10.1463
	W	10.7975	9.1686	13.4020	12.1649	13.2082	10.9470	12.4569	10.9623	13.4205	11.9724	18.5991	17.2300	15.0131	14.7765	9.6899	9.1857

		3-Dec		4-Dec		5-Dec		6-Dec		7-Dec		8-Dec		9-Dec		10-Dec	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	7.7090	7.4423	7.0569	6.9833	6.9404	6.5957	6.8107	6.3461	6.5956	6.2245	6.2690	5.8504	6.3136	6.0495	10.2753	10.0300
	N	14.5470	13.1418	13.7723	12.0581	13.5443	11.6773	11.8334	10.1177	9.6646	8.1311	7.0834	6.4586	6.2957	5.9625	6.0645	5.5210
	W	7.6470	6.4255	7.4820	6.8172	17.6987	17.5244	19.0386	18.8656	12.9715	12.7633	12.4191	12.0923	8.7724	8.2943	8.5334	7.8725

		11-Dec		12-Dec		13-Dec		14-Dec		15-Dec		16-Dec		17-Dec		18-Dec	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	10.2047	10.0881	8.1297	8.0495	7.0774	6.8503	5.5408	5.1575	5.2680	4.9749	5.0800	4.8578	4.8355	4.6512	4.5273	3.9280
	N	5.9890	5.8548	5.8178	5.1219	5.5535	4.7771	5.3236	4.5468	5.2430	4.8032	5.4179	4.4548	5.4994	4.6098	5.1485	4.4179
	W	7.6606	6.7058	7.7289	6.9705	9.2437	8.8601	11.7662	10.6656	9.9129	7.7021	8.6415	6.3430	12.1635	8.2762	16.5726	10.0614

		19-Dec		20-Dec		21-Dec		22-Dec		23-Dec		24-Dec		25-Dec		26-Dec	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	4.2104	3.4531	3.9201	3.6043	3.6634	3.2629	3.6055	3.3825	3.6101	3.0997	3.6785	3.3651	12.3746	9.8510	16.9485	13.7240
	N	5.1689	4.8500	5.8035	5.0492	5.5200	4.5101	5.6675	5.2047	5.7225	5.5381	5.6032	5.2028	5.3972	4.6826	6.4477	6.2730
	W	14.2411	5.9772	9.7876	1.3401	9.4439	1.2008	14.1592	5.8676	18.7559	10.5803	16.7408	8.2675	12.8848	5.2465	10.5072	3.6997

		27-Dec		28-Dec		29-Dec		30-Dec		31-Dec	
		Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized	Natural	Optimized
S	D	9.0385	6.3488	6.2471	6.1580	7.4868	7.2181	9.2409	9.1191	7.4150	7.2491
	N	7.0936	6.4533	6.9162	6.6080	7.8049	7.5119	6.0031	5.1185	5.8356	5.5903
	W	9.9852	4.7055	9.3109	6.4607	9.0359	6.4435	8.7571	7.2000	8.4092	7.8879

Appendix C

Supplementary Materials

Section A

Table S1. SPHY model (see Section "Scale and scenario setting") input type and their values for the generation of the surface runoff for the river network in the considered case study area.

Map		Source
Dem		Cantabrian Government/EU-DEM
Latitude		European Space Agency (ESA)
Top soil	*Field capacity* ($SW_{1,\,fc}$)	HiHydroSoil Database
	Saturated water content ($SW_{1,\,sat}$)	
	Wilting point ($SW_{1,\,pF3}$)	
	Permanent wilting point ($SW_{1,\,pF4.2}$)	
	Saturated conductivity ($K_{sat,\,1}$)	
Sub soil	*Field capacity* ($SW_{2,\,fc}$)	HiHydroSoil Database
	Saturated water content ($SW_{2,\,sat}$)	
	Saturated conductivity ($K_{sat,\,2}$)	
Land use		IHCantabria
Climate	*Precipitation*	IHCantabria
	Temperature (min, mean, max)	

Model parameter	Physical meaning of model parameter	Initial value
$SW_{3,\,sat}$	*Saturated water content in groundwater zone (mm)*	300
δ_{gw}	*Delay in groundwater recharge (days)*	119.697
BF_{tresh}	*Minimum value for baseflow to occur (mm)*	0
α_{gw}	*Parameter of baseflow days: alphaGw = 2.3/x (x = nr. Of baseflow days)*	0.051
μ	*Specific aquifer yield (m/m)*	0.05
kx	*Recession coefficient of routing*	0.5

Table S2. Variation of the environmental parameters for the present (1980-2012) and future (2041-2070) time periods considered in the study.

Basin	**P** (mm/year)	T_{mean} (ºC)	**Kc**	**ETa** (mm/year)	Q_{mean} (m^3/s)
1980-2012	**1531**	**8.5**	**0.78**	**566**	**13.20**
2041-2070	**1387**	**10.1**	**0.84**	**614**	**9.90**
Variation	**-9%**	**1.6ºC**	**8%**	**9%**	**-25%**

The hydrological model's performance during calibration was analysed based on the Nash-Sutcliffe efficiency (LOG NSE) between observed and simulated flow. The performance of the SPHY model in the Pas catchment was done using the Puente Viesgo gauge station (period 01/01/1996 to 31/12/1998) and showed good calibration performance (log NSE =0.74). In addition, the model validation was assessed based on the LOG NSE and the percentage of Bias (PBIAS) from the observed mean flow. The validation analysis was done using the Puente Viesgo gauge station data for the period 01/01/1980 to 30/09/2007 and the results (LOG NSE = 0.75 and PBIAS = -7.28) confirmed the validity of the parameter values established through the calibration process.

Table S3. Percentage cover for each class and each scenario considered in the optimization simulation.

Land cover type	**PR Baseline**	**CC_BAU**	**CC_BGIN**
Broadleaf forest	16%	18%	25%
Coniferous forest	3%	3%	3%
Scrubs and Shrubs	45%	55%	48%
Pasture and grassland	29%	18%	19%
Agricultural land	4%	3%	2%
Denuded rock, bare land	0,5%	0,5%	0,5%
Urban areas & Human-derived activities	3%	3%	3%
Wetlands and water-associated ecosystems	0,5%	0,5	0,5%

Table S4. Summary of the e-flow requirements (EFR) considered in the study. The EFR define the hydrological conditions to be conserved in the river during the daily diversion operations throughout the year. The table shows the duration, the hydrological metric used and the month of the year relevant for each EFR. Legend: %MMF = percentage value of mean monthly flow; Qm7 = 7 times the median annual flow; Q75 = the flow value that is exceeded 25% of the time; %MYF = percentage value of the mean yearly flow.

<table>
<tr><th colspan="2">Supporting ES</th><th>EFR</th><th>Duration</th><th>Oct</th><th>Nov</th><th>Dec</th><th>Jan</th><th>Feb</th><th>Mar</th><th>Apr</th><th>May</th><th>Jun</th><th>Jul</th><th>Aug</th><th>Sept</th></tr>
<tr><td>Provision of habitat conditions for fish ES</td><td>Migration</td><td>R1a</td><td>Month</td><td colspan="2">35% MMF</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td></td><td></td><td>R1b</td><td>2 events (1 per month)</td><td colspan="2">> Qm7</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td></td><td>Spawning</td><td>R2</td><td>Month</td><td></td><td></td><td colspan="2">50% MMF</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td></td><td>Hatching</td><td>R3a</td><td>Month</td><td></td><td></td><td></td><td></td><td colspan="3">55% MMF</td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td></td><td></td><td>R3b</td><td>27 days</td><td></td><td></td><td></td><td></td><td colspan="3">< Qm7</td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td></td><td>Recruitment</td><td>R4</td><td>Month</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td colspan="5">55% MMF</td></tr>
<tr><td>Life-supporting conditions for macroinvertebrates ES</td><td></td><td>R5</td><td>5 events</td><td colspan="6">> Q75</td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Primary productivity ES</td><td></td><td>R6</td><td>70 days</td><td></td><td></td><td></td><td></td><td></td><td></td><td colspan="6">> 10% MYF</td></tr>
</table>

Section B

S5. Human water supply objective

The aim of this objective O_S, is the maximization of the yearly water supplied for human use. No limitation to the water volume for human use has been set but rather the objective aims to identify the highest river water volume that can be extracted, meaning the delivery capacity of the river can be assessed.
The condition is valid for each point in the basin, hence accounting for the local volumetric capacity at each considered location in the basin. The objective function has hence been expressed as a minimization function of the difference between the total water volume provided by the river and the total diverted water from the river:

$$O_S: \quad \min\ f(y) = V_z^R - V_z^{\mathrm{D}} \tag{1}$$

Where:

V_z^{R}	total natural water volume per year that is available at a specific point z in the river, in m^3 per year;
V_z^{D}	total diverted water volume in m^3 per year, represents the maximum total abstraction volume per year at a specific point z (corresponding with a RS).

The total volume of natural flow and diverted flow is defined as follows:

$$V_z^R = \sum_{i=1}^{365}(x_i \cdot \tau) \tag{2}$$

$$V_z^D = \sum_{i=1}^{365}(y_i \cdot \tau) \tag{3}$$

Where:

$i \in \{1, \dots, 365\}$	days of the year;
x_i	natural flow (m^3/s) at day i of the year, $x_{\mathrm{i}} \in \mathbb{R}_0^+$. Represents the value of the natural flow (m^3/s) in the river at day i and is defined by the input scenario. This value doesn't change throughout the optimization process;
y_i	diverted flow (m^3/s) at day i of the year, $y_i \in \mathbb{R}_0^+$. Represents the portion of river flow (m^3/s) that is diverted from the river. It is randomly generated at each generation;
τ	constant, referring to the daily time-frame of diversion (considered 24 h);

Subject to:

Daily diverted discharge limit

$$0 \leq y_i \leq x_i \tag{4}$$

S6. Ecosystem services objectives

The ecosystem services (ES) objectives considered in this study: habitat conditions provisions for fish at different life-stages ES (O_{ES}^1), provision of conditions for macroinvertebrates taxa richness ES (O_{ES}^2) and primary productivity ES (O_{ES}^3) are represented by the aggregation of six optimization indicators (i.e. O_{R1}, O_{R2}, O_{R3}, O_{R4}, O_{R5}, O_{R6}). This section provides the description of the optimization functions defining the optimization indicators. The optimization equations presented below are expressed as minimization functions of the sum of the scores for each e-flow requirement. For modelling convenience each indicator has been fragmented in sub-equations, hence the equations are presented as they were incorporated in the optimization model.

Optimization objectives for habitat condition provision for fish life-stages ES (O_{ES}^1)

$$O_{ES}^1 = O_{R1} + O_{R2} + O_{R3} + O_{R4} \tag{5}$$

Let $q_i \coloneqq x_i - y_i$ be the residual water flow (m^3/s) in the river (the difference between x_i and y_i and represents the portion of the river flow that remains in the river after diversion), the O_{R1} optimization objective for fish migration is defined as follows:

$$O_{R1}: \quad \min f(q) = O_{R1}^1 + O_{R1}^2 + O_{R1}^3 \tag{6}$$

$$O_{R1}^1: \quad f_{1;1}(q) = \frac{\sum_{i=1}^{n} S_i^{R1;1}}{n} \qquad where\ i \in a_1 \tag{7}$$

$$S_i^{R1;1} = \begin{cases} 0, & \forall\ i,\ if\ q_i - \alpha_h^{35} > 0,\ i \in \mathscr{A}_1 \\ 1 - \frac{q_i}{\alpha_h^{35}}, & otherwise \end{cases} \tag{8}$$

Where:

$S_i^{R1;1}$	score value for the day i, when $i \in \mathscr{A}_1$;
$\mathscr{A}_1$	set of days of the year relevant for R1;1;
a_1	subset of $\mathscr{A}_1$, containing $S_i^{R1;1} > 0$ values;
n	number of days in the set a_1, $n \in \mathbb{N}^*$;
α_h^{35}	reference value for the discharge threshold (in m^3/s) corresponding to the 35% of the *mean monthly flow* value for the given hydrograph h.

$$O_{R1}^2: \quad f_{1;2}(q) = \frac{\sum_{i=1}^{n} S_i^{R1;2}}{n} \qquad where\ i \in a_2 \tag{9}$$

$$S_i^{R1;2} = \begin{cases} 0\,, & \forall\, i,\ if\ q_i - \alpha_h^{35} > 0,\ i \in \mathscr{A}_2 \\ 1 - \frac{q_i}{\alpha_h^{35}}, & otherwise \end{cases} \tag{10}$$

Where:

$S_i^{R1;2}$	score value for the day i, when $i \in \mathscr{A}_2$
$\mathscr{A}_2$	set of days of the year relevant for R1;2;
a_2	subset of $\mathscr{A}_2$, containing $S_i^{R1;2} > 0$ values
n	number of days in the set a_2, $n \in \mathbb{N}^*$;
α_h^{35}	reference value for the discharge threshold (in m^3/s) corresponding to the 35% of the *mean monthly flow* value for the given hydrograph h.

$$O_{R1}^3: \quad f_{1;3}(q) = S^{R1;3} \tag{11}$$

$$S^{R1;3} = \begin{cases} 0, & \forall\, i,\ if\ N^{R1;3} \geq \beta_R, i \in a_3 \\ \beta_h - \omega, & otherwise \end{cases} \tag{12}$$

$$N^{R1;3} = \sum_i I_{q_i \geq \beta_h} \qquad i \in \mathscr{A}_3 \tag{13}$$

Where:

$S^{R1;3}$	score value for the R1;3 ;
$N^{R1;3}$	number of days i, resulting from the set $\mathscr{A}_3$, that satisfy the condition;
$\mathscr{A}_3$	set of days of the year relevant for R1;3 ;
a_3	subset of $\mathscr{A}_3$, containing $S_i^{R1;3}$ values;
ω	max $f[\,a_3]$ is the maximum of the set a_3;
I	indicator function, takes the value of 1 or 0 respectively if the condition is satisfied or not;
β_h	reference value for the discharge threshold (in m^3/s) corresponding to seven times the median annual flow value for the given hydrograph h;
β_R	constant, number representing the optimal occurrence of events for the promotion of R1;3, $\beta_R \in \mathbb{N}^*$;

The O_{R2} optimization objective for fish spawning is defined as follows:

$$O_{R2}: \quad \min\, f(q) = O_{R2}^1 + O_{R2}^2 \tag{14}$$

$$O_{R2}^1: \quad f_{2;1}(q) = \frac{\sum_{i=1}^{n} S_i^{R2;1}}{n} \qquad where\ i \in b_1 \tag{15}$$

$$S_i^{R2;1} = \begin{cases} 0\,, & \forall\, i,\ if\ q_i - \alpha_h^{50} > 0,\ i \in \mathscr{B}_1 \\ 1 - \frac{q_i}{\alpha_h^{50}}, & otherwise \end{cases} \tag{16}$$

Where:

$S_i^{R2;1}$	score value for the day i, when $i \in \mathscr{B}_1$;
$\mathscr{B}_1$	set of days of the year relevant for R2;1;
b_1	subset of $\mathscr{B}_1$, containing $S_i^{R2;1} > 0$ values;
n	number of days in the set b_1, $n \in \mathbb{N}^*$;

α_h^{50}	reference value for the discharge threshold (in m^3/s) corresponding to the 50% of the *mean monthly flow* value for the given hydrograph h.

$$O_{R2}^2: \quad f_{2;2}(q) = \frac{\sum_{i=1}^{n} S_i^{R2;2}}{n} \qquad where\ i \in b_2 \tag{17}$$

$$S_i^{R2;2} = \begin{cases} 0, & \forall\, i,\ if\ q_i - \alpha_h^{50} > 0,\ i \in \mathscr{B}_2 \\ 1 - \frac{q_i}{\alpha_h^{50}}, & otherwise \end{cases} \tag{18}$$

Where:

$S_i^{R2;2}$	score value for the day i, when $i \in \mathscr{B}_2$;
$\mathscr{B}_2$	set of days of the year relevant for R2;2;
b_2	subset of $\mathscr{B}_2$, containing $S_i^{R2;2} > 0$ values;
n	number of days in the set b_2, $n \in \mathbb{N}^*$;
α_h^{50}	reference value for the discharge threshold (in m^3/s) corresponding to the 50% of the *mean monthly flow* value for the given hydrograph h.

The O_{R3} optimization objective for fish hatching is defined as follows:

$$O_{R3}: \quad \min f(q) = O_{R3}^1 + O_{R3}^2 + O_{R3}^3 + O_{R3}^4 \tag{19}$$

$$O_{R3}^1: \quad f_{3;1}(q) = \frac{\sum_{i=1}^{n} S_i^{R3;1}}{n} \qquad where\ i \in c_1 \tag{20}$$

$$S_i^{R3;1} = \begin{cases} 0, & \forall\, i,\ if\ q_i - \alpha_h^{55} > 0,\ i \in \mathscr{C}_1 \\ 1 - \frac{q_i}{\alpha_h^{55}}, & otherwise \end{cases} \tag{21}$$

Where:

$S_i^{R3;1}$	score value for the day i, when $i \in \mathscr{C}_1$;
$\mathscr{C}_1$	set of days of the year relevant for R3;1;
c_1	subset of $\mathscr{C}_1$, containing $S_i^{R3;1} > 0$ values;
n	number of days in the set c_1, $n \in \mathbb{N}^*$;
α_h^{55}	reference value for the discharge threshold (in m^3/s) corresponding to the 55% of the *mean monthly flow* value for the given hydrograph h.

$$O_{R3}^2: \quad f_{3;2}(q) = \frac{\sum_{i=1}^{n} S_i^{R3;2}}{n} \qquad where\ i \in c_2 \tag{22}$$

$$S_i^{R3;2} = \begin{cases} 0, & \forall\, i,\ if\ q_i - \alpha_h^{55} > 0,\ i \in \mathscr{C}_2 \\ 1 - \frac{q_i}{\alpha_h^{55}}, & otherwise \end{cases} \tag{23}$$

Where:

$S_i^{R3;2}$	score value for the day i, when $i \in \mathscr{C}_2$;
$\mathscr{C}_2$	set of days of the year relevant for R3;2;
c_2	subset of $\mathscr{C}_2$, containing $S_i^{R3;2} > 0$ values;
n	number of days in the set c_2, $n \in \mathbb{N}^*$;

α_h^{55}	reference value for the discharge threshold (in m³/s) corresponding to the 55% of the *mean monthly flow* value for the given hydrograph h.

$$O_{R3}^3: \quad f_{3;3}(q) = \frac{\sum_{i=1}^{n} S_i^{R3;3}}{n} \qquad where\ i \in c_3 \tag{24}$$

$$S_i^{R3;3} = \begin{cases} 0\,, & \forall\, i,\ if\ q_i - \alpha_h^{55} > 0,\ i \in \mathscr{C}_3 \\ 1 - \frac{q_i}{\alpha_h^{55}}, & otherwise \end{cases} \tag{25}$$

Where:

$S_i^{R3;3}$	score value for the day i, when $i \in \mathscr{C}_3$;
$\mathscr{C}_3$	set of days of the year relevant for R3;3;
c_3	subset of $\mathscr{C}_3$, containing $S_i^{R3;3} > 0$ values;
n	number of days in the set c_3, $n \in \mathbb{N}^*$;
α_h^{55}	reference value for the discharge threshold (in m³/s) corresponding to the 55% of the *mean monthly flow* value for the given hydrograph h.

$$O_{R3}^4: \quad f_{3;4}(q) = w_c - S_{i+w}^{R3;4} \qquad where\ i + w \in \mathscr{C}_4 \tag{26}$$

$$S_{i+w}^{R3;4} = \begin{cases} w_c, & if\ N^{R3;4} \geq w_c \\ N^{R3;4}, & otherwise \end{cases} \tag{27}$$

$$N^{R3;4} = \sum_{i+w} I_{q_{i+w} \geq \beta_h} \qquad i + w \in \mathscr{C}_4,\ w \in \{0, \ldots, 27\} \tag{28}$$

Where:

$S_{i+w}^{R3;4}$	reference factor for fish hatching score;
$N_{i+w}^{R3;4}$	number of days i, when $i + w \in \mathscr{C}_4$, that satisfy the condition;
$\mathscr{C}_4$	set of days of the year relevant for R3;4 ;
I	indicator function, takes the value of 1 or 0 respectively if the condition is satisfied or not;
w	number of consecutive days representing the optimal time length for R3;4;
w_c	constant, target number of days for R3;4;
β_h	reference value for the discharge threshold (in m³/s) corresponding to seven times the median annual flow (7mQ) for the given hydrograph h.

The O_{R4} optimization objective for fish recruitment is defined as follows:

$$O_{R4}: \quad \min\ f(q) = O_{R4}^1 + O_{R4}^2 + O_{R4}^3 + O_{R4}^4 + O_{R4}^5 \tag{29}$$

$$O_{R4}^1: \quad f_{4;1}(q) = \frac{\sum_{i=1}^{n} S_i^{R4;1}}{n} \qquad where\ i \in d_1 \tag{30}$$

$$S_i^{R4;1} = \begin{cases} 0\,, & \forall\, i,\ if\ q_i - \alpha_h^{55} > 0,\ i \in \mathscr{D}_1 \\ 1 - \frac{q_i}{\alpha_h^{55}}, & otherwise \end{cases} \tag{31}$$

Where:

$S_i^{R4;1}$	score value for the day i, when $i \in \mathscr{D}_1$;

$\mathscr{D}_1$	set of days of the year relevant for R4;1;
d_1	subset of $\mathscr{D}_1$, containing $S_i^{R4;1} > 0$ values;
n	number of days in the set d_1, $n \in \mathbb{N}^*$;
α_h^{55}	reference value for the discharge threshold (in m^3/s) corresponding to the 55% of the *mean monthly flow* value for the given hydrograph h.

$$O_{R4}^2: \quad f_{4;2}(q) = \frac{\sum_{i=1}^{n} S_i^{R4;2}}{n} \qquad where\ i \in d_2 \tag{32}$$

$$S_i^{R4;2} = \begin{cases} 0, & \forall\ i,\ if\ q_i - \alpha_h^{55} > 0,\ i \in \mathscr{D}_2 \\ 1 - \frac{q_i}{\alpha_h^{55}}, & otherwise \end{cases} \tag{33}$$

Where:

$S_i^{R4;2}$	score value for the day i, when $i \in \mathscr{D}_2$;
$\mathscr{D}_2$	set of days of the year relevant for R4;2;
d_2	subset of $\mathscr{D}_2$, containing $S_i^{R4;2} > 0$ values;
n	number of days in the set d_2, $n \in \mathbb{N}^*$;
α_h^{55}	reference value for the discharge threshold (in m^3/s) corresponding to the 55% of the *mean monthly flow* value for the given hydrograph h.

$$O_{R4}^3: \quad f_{4;3}(q) = \frac{\sum_{i=1}^{n} S_i^{R4;3}}{n} \qquad where\ i \in d_3 \tag{34}$$

$$S_i^{R4;3} = \begin{cases} 0, & \forall\ i,\ if\ q_i - \alpha_h^{55} > 0,\ i \in \mathscr{D}_3 \\ 1 - \frac{q_i}{\alpha_h^{55}}, & otherwise \end{cases} \tag{35}$$

Where:

$S_i^{R4;3}$	score value for the day i, when $i \in \mathscr{D}_3$;
$\mathscr{D}_3$	set of days of the year relevant for R4;3;
d_3	subset of $\mathscr{D}_3$, containing $S_i^{R4;3} > 0$ values;
n	number of days in the set d_3, $n \in \mathbb{N}^*$;
α_h^{55}	reference value for the discharge threshold (in m^3/s) corresponding to the 55% of the *mean monthly flow* value for the given hydrograph h.

$$O_{R4}^4: \quad f_{4;4}(q) = \frac{\sum_{i=1}^{n} S_i^{R4;4}}{n} \qquad where\ i \in d_4 \tag{36}$$

$$S_i^{R4;4} = \begin{cases} 0, & \forall\ i,\ if\ q_i - \alpha_h^{55} > 0,\ i \in \mathscr{D}_4 \\ 1 - \frac{q_i}{\alpha_h^{55}}, & otherwise \end{cases} \tag{37}$$

Where:

$S_i^{R4;4}$	score value for the day i, when $i \in \mathscr{D}_4$;
$\mathscr{D}_4$	set of days of the year relevant for R4;4;

d_4	subset of $\mathscr{D}_4$, containing $S_i^{R4;4} > 0$ values;
n	number of days in the set d_4, $n \in \mathbb{N}^*$;
α_h^{55}	reference value for the discharge threshold (in m^3/s) corresponding to the 55% of the *mean monthly flow* value for the given hydrograph h.

$$O_{R4}^5: \quad f_{4;5}(q) = \frac{\sum_{i=1}^{n} S_i^{R4;5}}{n} \qquad where\ i \in d_5 \tag{38}$$

$$S_i^{R4;5} = \begin{cases} 0, & \forall\ i,\ if\ q_i - \alpha_h^{55} > 0,\ i \in \mathscr{D}_5 \\ 1 - \frac{q_i}{\alpha_h^{55}}, & otherwise \end{cases} \tag{39}$$

Where:

$S_i^{R4;5}$	score value for the day i, when $i \in \mathscr{D}_5$;
$\mathscr{D}_5$	set of days of the year relevant for R4;5;
d_5	subset of $\mathscr{D}_5$, containing $S_i^{R4;5} > 0$ values;
n	number of days in the set d_5, $n \in \mathbb{N}^*$;
α_h^{55}	reference value for the discharge threshold (in m^3/s) corresponding to the 55% of the *mean monthly flow* value for the given hydrograph h.

Optimization objective for hydrological conditions for macroinvertebrates' taxa richness ES (O_{ES}^2)

The O_{ES}^2 corresponds to the value of the O_{R5}:

$$O_{R5}: \quad \min f(q) = 1 - \frac{S^{R5}}{\gamma_R} \qquad i \in \mathscr{E} \tag{40}$$

$$S^{R5}: \quad f_5(q) = \begin{cases} \gamma_R, & if\ N^{R5} \geq \gamma_R, i \in \mathscr{E} \\ N^{R5}, & otherwise \end{cases} \tag{41}$$

$$N^{R5} = \sum_i I_{q_i \geq \gamma_h} \qquad i \in \mathscr{E} \tag{42}$$

Where:

S_i^{R5}	reference factor for R5;
N^{R5}	number of days i, when $i \in \mathscr{E}$ that satisfy the condition;
I	indicator function, takes the value of 1 or 0 respectively if the condition is satisfied or not;
$\mathscr{E}$	set of days of the year relevant for R5;
γ_R	constant, number representing the optimal occurrence of events for the promotion of R5, $\gamma_R \in \mathbb{N}^*$;
γ_h	reference value for the discharge threshold (in m^3/s) corresponding to the *75-percentile flow (Q25)* value for the given hydrograph h.

Optimization objective for primary productivity ES (O_{ES}^3)

The O_{ES}^3 corresponds to the value of the O_{R6}:

$$O_{R6}: \quad \min\ f(q) = 1 - \frac{S_{i+u}^{R6}}{\sigma_R} \qquad i+u \in \mathscr{F} \tag{43}$$

$$S_{i+u}^{R6}: \quad f_6(q) = \begin{cases} \sigma_R, & if\ N^{R6} \geq \sigma_R, i+u \in \mathscr{F} \\ N^{R6}, & otherwise \end{cases} \tag{44}$$

$$N^{R6} = \sum_i I_{q_i+u \geq \sigma_h^{10}} \qquad i+u \in \mathscr{F},\ u \in \{0, \ldots, 70\} \tag{45}$$

Where:

R_{i+u}^{R6}	reference factor for R6;
N^{R6}	total number of days i, when $i+u \in \mathscr{F}$, that satisfy the condition;
I	indicator function, takes the value of 1 or 0 respectively if the condition is satisfied or not;
u	range of days representing the optimal time length for R6;
$\mathscr{F}$	set of days of the year relevant for macrophytes seedling survival;
σ_R	constant, number representing the optimal number of days for the promotion of primary producers density and growth, $\sigma_R \in \mathbb{N}^*$;
σ_h^{10}	reference value for the discharge threshold (in m^3/s) corresponding to the *10% of the average yearly flow* calculated from the historical flow record.

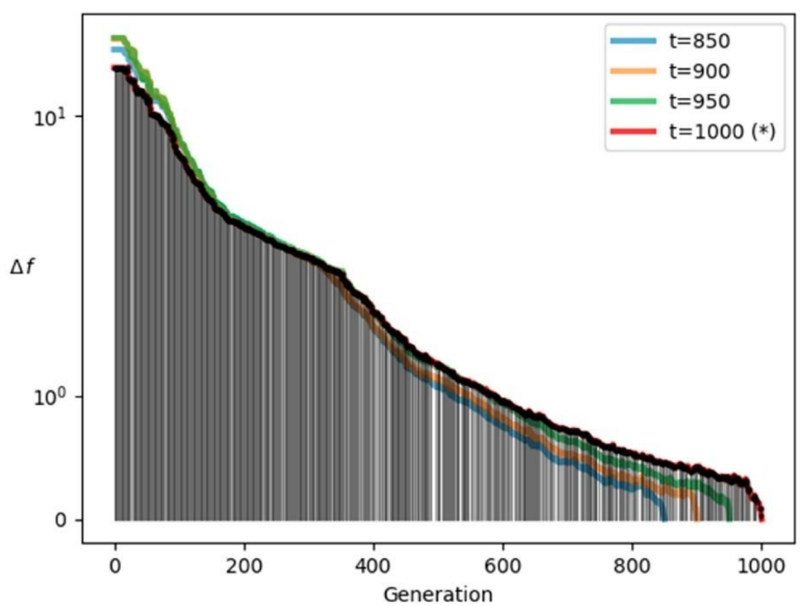


Figure S1. The Running Metric Indicator (Blank & Deb, 2020) for a test RS simulation. The Δf indicator measures the convergence of the objective space at each generation.

Section C

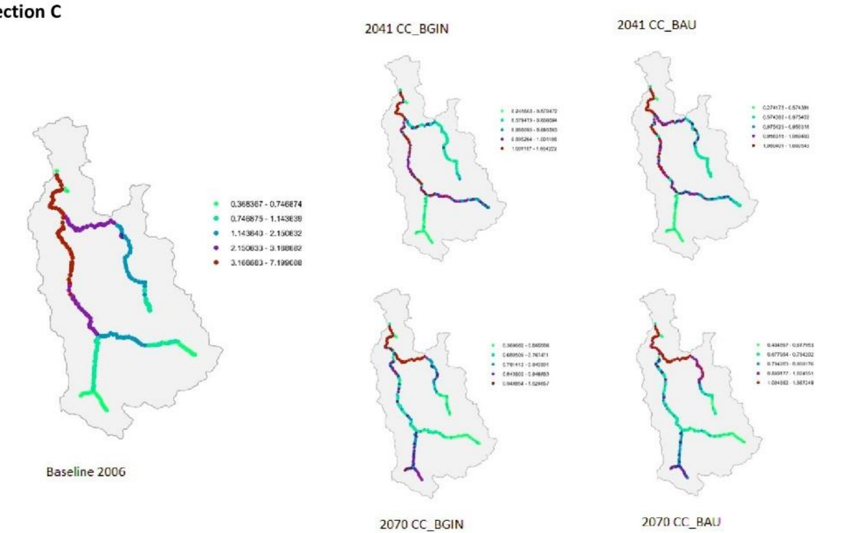


Figure S2. Maps showing the spatial distribution of the optimization objective scores for the *Habitat condition provision for fish life-stages ES* under each considered scenario. Values closest to zero indicate best achievement of the objective at a specific RS. The classification scheme follows the quantile chromatic classification approach: Red shades = highest scores (worst results), light-green shades = lowest scores (best results). Note: each map presents min-max values that differ from each other as figure aim is to highlight scenario-specific spatial variation of the scores.

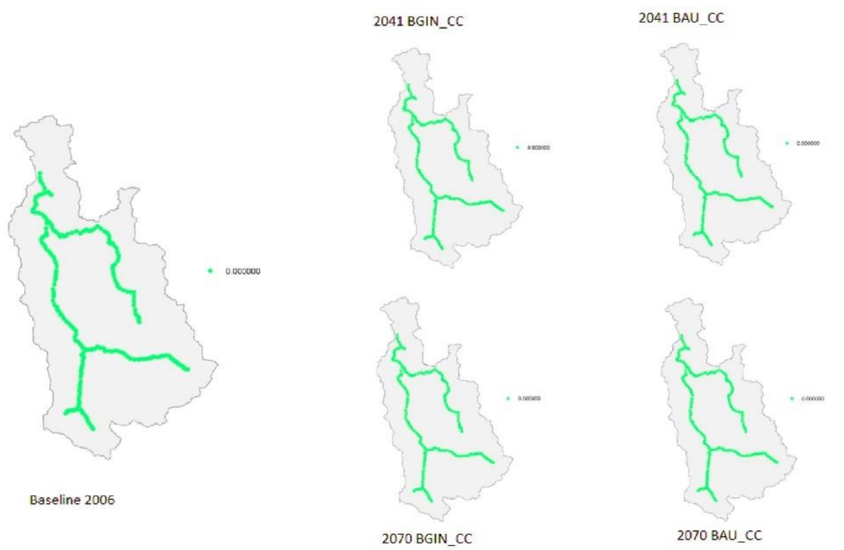


Figure S3. Maps showing the spatial distribution of the optimization objective scores for the life-supporting conditions for *Macroinvertebrate taxa richness ES* under each considered scenario. Values closest to zero indicate best achievement of the objective at a specific RS.

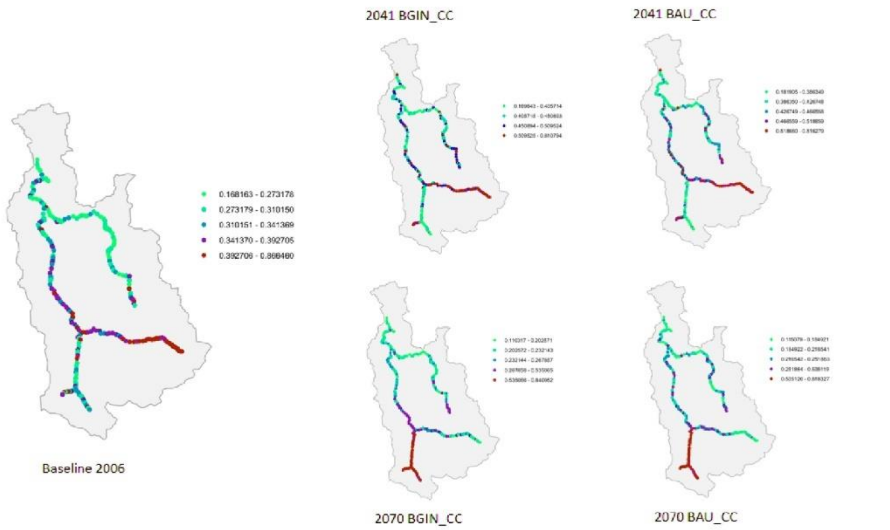


Figure S4. Maps showing the spatial distribution of the optimization objective scores for the *Primary productivity ES* under each considered scenario. Values closest to zero indicate best achievement of the objective at a specific RS. The classification scheme follows a quantile chromatic classification approach: Red shades = highest scores (worst results), light-green shades = lowest scores (best results). Note: each map presents min-max values that differ from each other as figure aim is to highlight scenario-specific spatial variation of the scores.

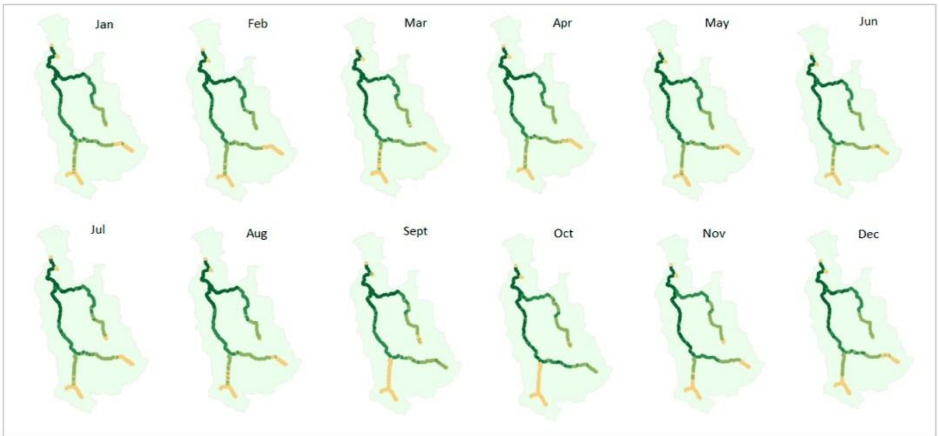


Figure S5. Monthly averaged optimized instream flow for the PR scenario (2006) using the quantile (25-100%) classification method: yellow=low discharge values; dark green=high discharge values).

Figure S6. Monthly averaged optimized instream flow for the CC_BAU 2041 scenario using the quantile (25-100%) classification method: yellow=low discharge values; dark green=high discharge values).

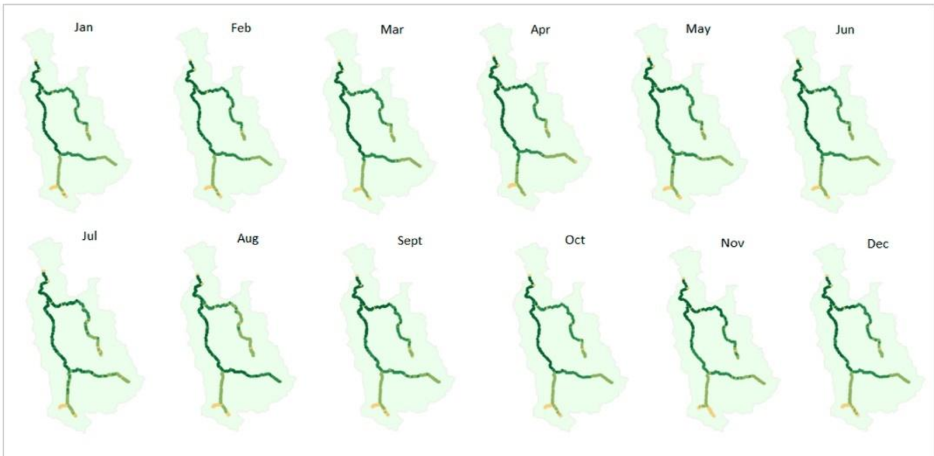


Figure S7. Monthly averaged optimized instream flow for the CC_BGIN 2041 scenario using the quantile (25-100%) classification method: yellow=low discharge values; dark green=high discharge values).

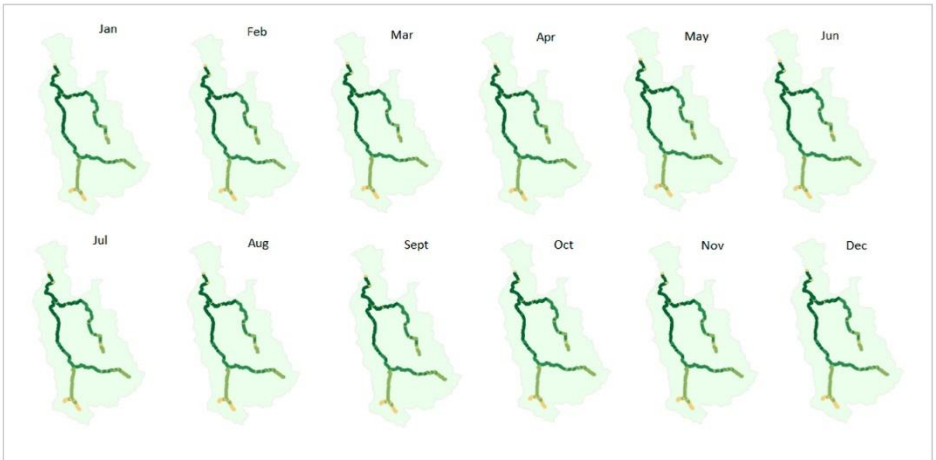


Figure S8. Monthly averaged optimized instream flow for the CC_BGIN 2070 scenario using the quantile (25-100%) classification method: yellow=low discharge values; dark green=high discharge values).

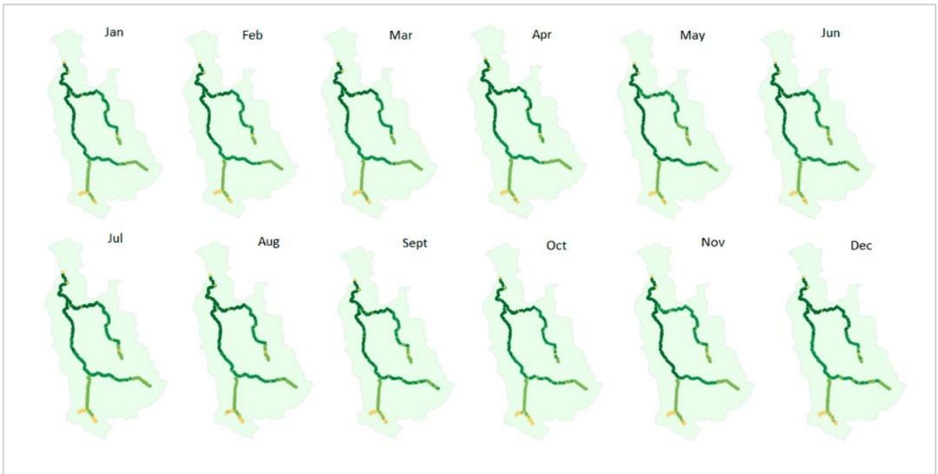


Figure S9. Monthly averaged optimized instream flow for the CC_BAU 2070 scenario using the quantile (25-100%) classification method: yellow=low discharge values; dark green=high discharge values).

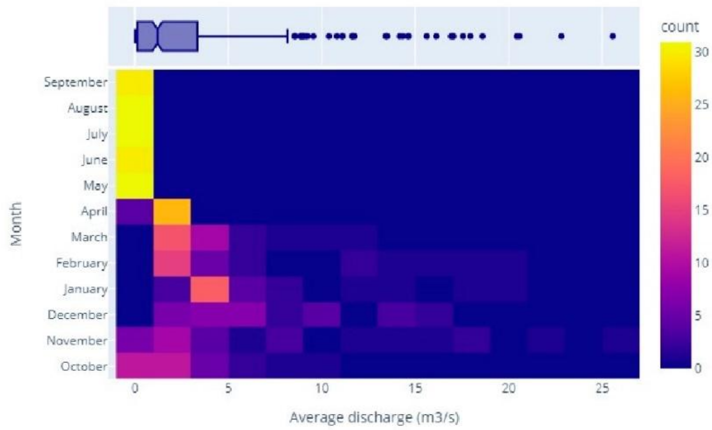


Figure S10. Heatmap showing the average optimized discharge (in m3/s) value (on the x-axis) for each month (on the y-axis) for the 2041 BGIN_CC scenario. On the right-hand side of the box a colour-based classification of the frequency of appearance of each value range; on top of the box a regular box-plot shows the yearly quartiles, extremes and outliers.

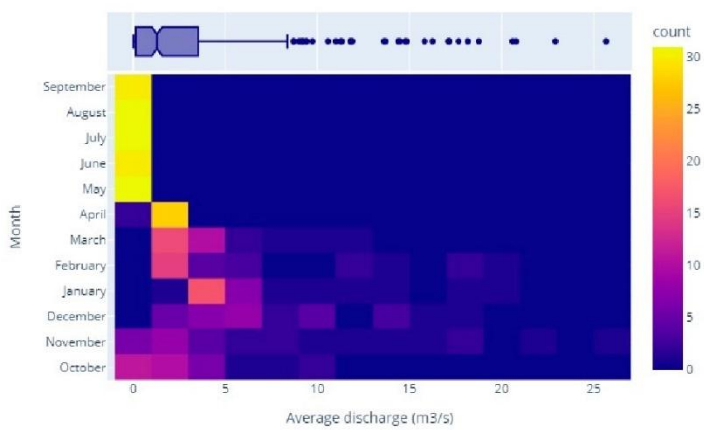


Figure S11. Heatmap showing the average optimized discharge (in m3/s) value (on the x-axis) for each month (on the y-axis) for the 2041 BAU_CC scenario. On the right-hand side of the box a colour-based classification of the frequency of appearance of each value range; on top of the box a regular box-plot shows the yearly quartiles, extremes and outliers.

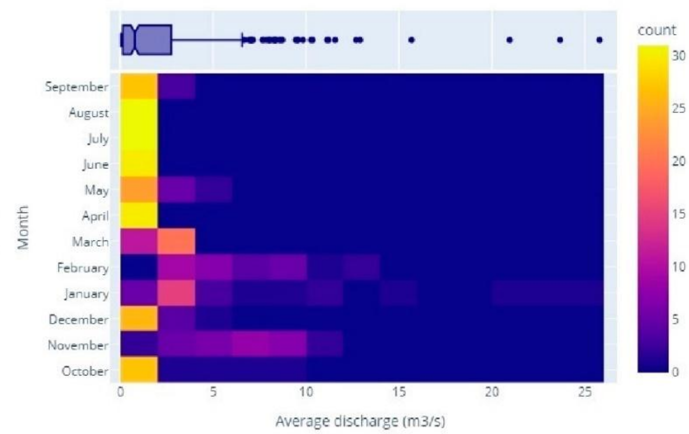


Figure S12. Heatmap showing the average optimized discharge (in m3/s) value (on the x-axis) for each month (on the y-axis) for the 2070 BGIN_CC scenario. On the right-hand side of the box a colour-based classification of the frequency of appearance of each value range; on top of the box a regular box-plot shows the yearly quartiles, extremes and outliers.

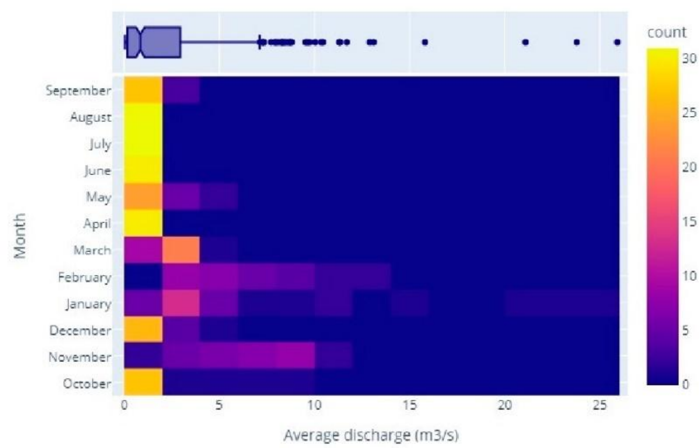


Figure S13. Heatmap showing the average optimized discharge (in m3/s) value (on the x-axis) for each month (on the y-axis) for the 2070 BAU_CC scenario. On the right-hand side of the box a colour-based classification of the frequency of appearance of each value range; on top of the box a regular box-plot shows the yearly quartiles, extremes and outliers.

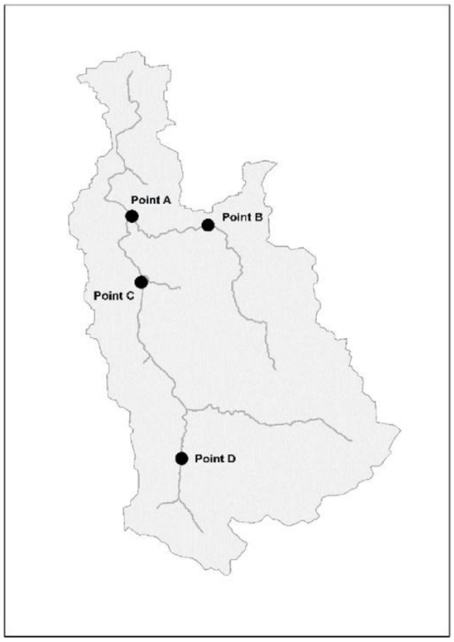
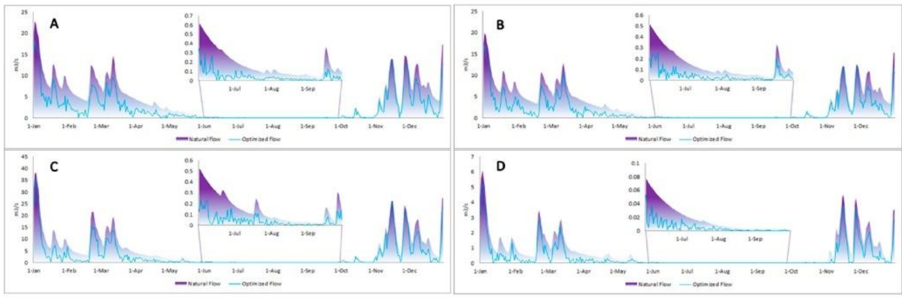
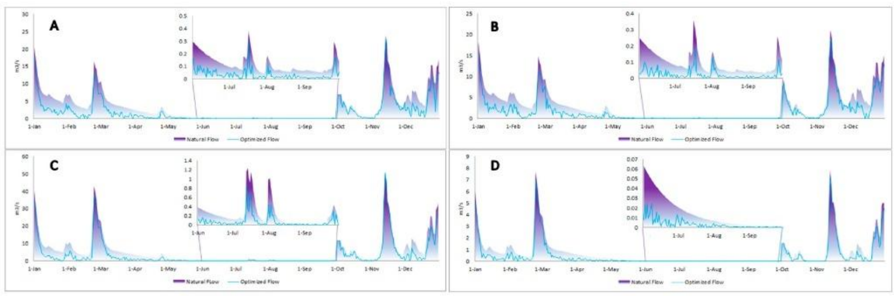


Figure S14. Location of the representative points in the basin elicited for results presentation and discussion. Complete optimization results available at : https://doi.org/10.6084/m9.figshare.19636449.v4



Figures S15-S16. Flow series showing the daily profile of the discharge (in m3/s) optimized for diversion (light blue thin line) plotted with respect to the river natural discharge (purple background shape) for the each of the four RS locations analyzed under the Baseline 2006 (PR) scenario (top) and 2041 BAU_CC scenario (bottom). More pronounced differences between the lines indicate the highest trade-off periods between the natural discharge and water for municipal use.



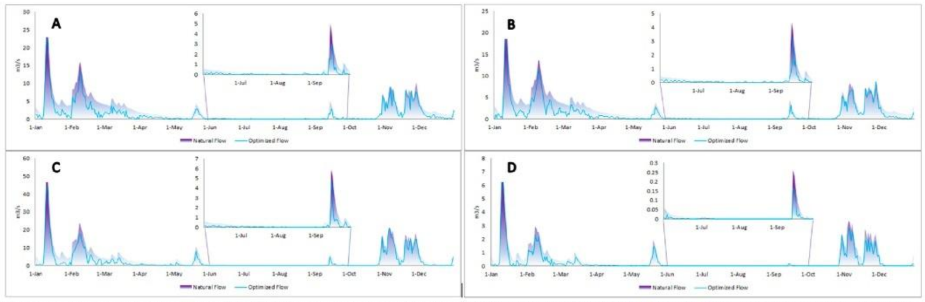
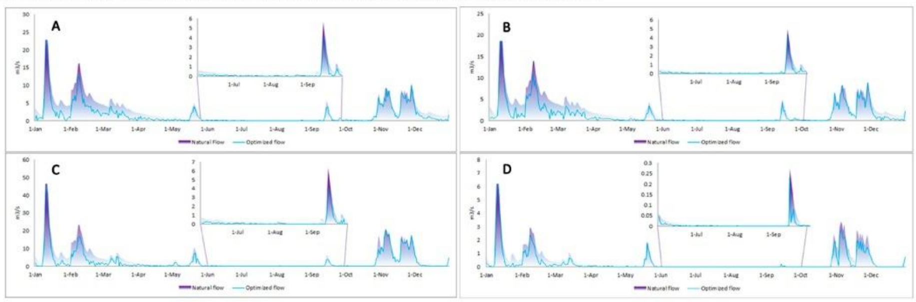


Figure S17-S18. Flow series showing the daily profile of the discharge (in m3/s) optimized for diversion (light blue thin line) plotted with respect to the river natural discharge (purple background shape) for the each of the four RS locations analyzed under the 2070 BGIN_CC (top) and 2070 BAU_CC scenario (bottom). More pronounced differences between the lines indicate the highest trade-off periods between the natural discharge and water for municipal use.



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Professional Background

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2018	EU Project Management Consultant *Consulta Europa Projects and Innovation Ltd, Las Palmas de Gran Canaria, Spain*
2017	Master's Degree in Environmental Sciences *Ca' Foscari University of Venice, Italy*
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Publications (peer-reviewed)

1. **Derepasko, D.**, Guillaume, J. H. A., Horne, A. C., & Volk, M. (2021). Considering scale within optimization procedures for water management decisions: Balancing environmental flows and human needs. *Environmental Modelling & Software*, *139*, 104991. https://doi.org/10.1016/j.envsoft.2021.104991
2. **Derepasko, D.**, Peñas, F.J., Barquín, J., & Volk, M. (2021). Applying Optimization to Support Adaptive Water Management of Rivers. *Water*, *13*(9), 1281. https://doi.org/10.3390/w13091281
3. Furlan, E., **Derepasko, D.**, Torresan, S., Pham, H. V., Fogarin, S., Critto, A. (2022). Ecosystem services at risk in Italy from coastal inundation under extreme sea level scenarios up to 2050: A spatially resolved approach supporting climate change adaptation, *Integrated Environmental Assessment and Management*, Volume 18, Issue 6, 1 November 2022, Pages 1564–1577. https://doi.org/10.1002/ieam.4620
4. **Derepasko, D.**, Witing, F., Peñas, F.J., Barquín, J., & Volk, M. (2023). Towards Adaptive Water Management—Optimizing River Water Diversion at the Basin Scale under Future Environmental Conditions. *Water, 15*(18), 3289. https://doi.org/10.3390/w15183289

Conferences

2020	International Symposium on Ecohydraulics (ISE) *Virtual*
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