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Leverage Points and Cascading Impacts Analysis in Nexus Systems Using System Dynamics Modeling

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Key Points:

- The Nexus approach is fundamental for managing eco-socio-hydrological systems but translating it into actionable policies is challenging
- Leverage points play a strategic role in managing Nexus systems, especially when their dynamic and uncertain nature is considered
- System Dynamics modeling supports the identification and management of leverage points and cascading impacts

Supporting Information:

Supporting Information may be found in the online version of this article.

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Abstract Operationalizing the Water-Ecosystem-Food (WEF) Nexus approach for sustainable resource management is challenging due to the complexity, non-linearity, and uncertainty of interconnected resources systems. A promising strategy requires identifying leverage points, namely key elements and processes where interventions can generate significant systemic change. However, leverage points are often difficult to discover and typically treated as static nodes rather than evolving and uncertain. To overcome this gap, qualitative and quantitative System Dynamics modeling tools are combined with other system-analysis methods. Unlike traditional approaches, the proposed modeling framework analyses leverage points as key dynamic elements, links, and feedback loops that activate and shift in intensity based on system state. The modeling process, applied to the Pinios River Basin (PRB) in Greece, helped revealing critical leverage points, including factors such as groundwater quality and agricultural productivity, key causal influences like the impact of natural areas' condition on agrotourism, and relevant feedback loops, such as the reinforcing dynamic driving the decline of natural areas. Deterministic and stochastic simulations contributed to validate the robustness of the modeling framework, with stochastic methods providing additional insights into the variability and uncertainty of system behavior. Recurring leverage points across simulations proved essential to drive effective management during critical transitions. Beyond the PRB, this modeling process provides a versatile framework for understanding and managing complex multi-sector systems, applicable to different contexts to support strategic decision-making toward sustainability and cascading impacts mitigation.

Plain Language Summary The complexity of the environment we live in is mainly due to the presence of multiple dynamics, such as water demand/use, ecosystems state, food production, which often interact in unpredictable ways. Effectively understanding and managing these dynamics requires holistic modeling approaches like those based on the concept of "Nexus", which focuses on the interactions among and within systems. The main issue is translating the theory behind the Nexus approach into practice. A promising solution is to identify leverage points, that is, critical areas of the system where changes can create big cascading impacts. However, these points are often treated as static, rather than as evolving dynamically and uncertainly over time. This work proposes a new modeling approach based on System Dynamics modeling and system-analysis tools to overcome this gap. Showing an application to a specific case study, the research underlines the versatility of the modeling process in identifying leverage points and analyzing cascading impact, making it applicable to different situations and decision-making processes.

1. Introduction

1.1. Challenges in "Nexus" Approach Operationalization

The Nexus approach has received significant attention in recent years because of its ability to consider interdependencies and synergies across different sectors, such as water, energy/ecosystems, and food (WEF), as well as human-nature interactions (Albrecht et al., 2018; Giordano et al., 2025; Grady et al., 2023; Teutschbein et al., 2023). This provides a holistic framework to support decision-making in eco-socio-hydrological systems (Biggs et al., 2021; Jiang & Simonovic, 2025).

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Notwithstanding these theoretical benefits of the Nexus approach, its operationalization into actionable policies is challenging (Dargin et al., 2019; Ramos et al., 2022). One difficulty is related to understanding the complexity of WEF Nexus systems. The complexity arises from interconnected components operating across different scales (Wiek et al., 2012). Another difficulty is the non-linearity of WEF Nexus systems due to the role of feedback loops and time delays, which causes disproportionate system responses, thus complicating their effective management (de Vos et al., 2019; Sivapalan et al., 2012). Based on that, modeling approaches that handle non-linearity, feedback loops and trade-offs across sectors are required to address these dynamics (Mirchi et al., 2012; Pande & Savenije, 2016; Simonovic & Breach, 2023). System Dynamics (SD) modeling is increasingly used for its ability to manage Nexus complexity and non-linearity. Using tools like Causal Loop Diagrams (CLDs) and Stock and Flow (SF) models, SD modeling supports the identification of feedback loops, synergies, and key structures of the systems as well as the simulation of responses to policies and external drivers (Laspidou et al., 2020; Sterman, 2000). This makes SD modeling suited for the analysis of cross-sectoral interdependencies and their cascading impacts (Wu et al., 2021).

Another important challenge in designing sustainable WEF Nexus systems is dealing with uncertainty (Calderon-Ambelis & Keshwani, 2022), which can stem from two principal sources: epistemic and aleatory (Beven, 2016; Di Baldassarre et al., 2016). The former arises from knowledge gaps on systems dynamics; the latter from the inherent randomness of environmental and social factors in Nexus systems (Kwakkel et al., 2010; Montanari, 2011). Even in the presence of abundant data, the sochastic nature of Nexus systems means that a degree of unpredictability always remains (Mekonnen et al., 2018). Uncertainty propagates within Nexus systems through their interconnections; moreover, feedback loops, cross-sectoral interactions, and non-linearities amplify or dampen effects (Tabandeh et al., 2022). Traditional modeling approaches for Nexus systems management often fail to fully address both epistemic and aleatory uncertainty or their propagation. Typically focused on external factors such as climate scenarios, traditional approaches have historically overlooked internal interactions that can intensify or mitigate effects (Maier et al., 2016). As a result, system management has run the risk of being caught off guard due to unintended and unforeseen consequences. Therefore, to effectively manage uncertainty in Nexus systems, integrated and cross-sectoral modeling approaches are needed. Stochastic methods coupled with SD modeling can perform this function thanks to their ability to explore multiple scenarios and account for uncertainty propagation. In this way, decision-makers are provided with a more holistic understanding of potential system outcomes (Terzi et al., 2021).

1.2. Leverage Points Identification as a Strategy for Managing Nexus Systems

One promising strategy in the management of WEF Nexus systems is to identify leverage points. These are key places or processes within the system where small changes can lead to significant effects at the system level (Forrester, 1971a; Meadows, 1999). Their identification can support dealing with the complexity of systems, which makes it complicated to understand how interventions in one sector affect the others (Bryant & Thomson, 2020; Kellner, 2023). They also support the management of non-linear dynamics through either the dampening of harmful feedback loops or the amplification of positive ones (Leventon et al., 2021; Murphy, 2022). For instance, pursuing economic growth may in some contexts generate problems such as poverty or pollution. This highlights that knowledge of system feedback loops is fundamental to avoid undesirable effects (Forrester, 1971b).

However, uncertainty in Nexus systems conditions the identification of leverage points. In fact, they may behave unpredictably, thus changing their effectiveness under changing conditions (Liu et al., 2007). To give an example, a leverage point that positively affects water management in one condition might lose impact if the system structure or external conditions shift unexpectedly. To ensure that leverage points remain effective under uncertain systems behaviors, randomness should be incorporated into the analysis of WEF Nexus systems.

Identifying such "sensitive spots" (Forrester, 1971a), however, tends to be counterintuitive and difficult. To support their identification, Meadows (1999) formally categorized leverage points into "shallow" and "deep" according to their level of influence on SD. Shallow leverage points are easy to manipulate, but they can only generate incremental changes. On the other hand, deep leverage points are difficult to control, but they can create transformational changes in the system (Loehr & Becken, 2021).

Although Meadows' guidelines have inspired significant works on the topic (see e.g., Birney, 2021; Dorninger et al., 2020; Leventon et al., 2021; Rosengren et al., 2023; Tenza-Peral et al., 2022), researchers have provided more structured methods to effectively identify leverage points within complex systems. Examples include Videira et al. (2014), who combined CLDs and Impact Matrices to map system structures and provide more quantitative insights into SD. This approach was then expanded by Murphy and Jones (2020) using Centrality Measures based on Graph Theory (e.g., degree centrality, closeness centrality, betweenness centrality, eigenvector centrality). Egerer et al. (2021) used weighting systems to identify important intervention entries, while Lam et al. (2021) used Centrality Measures to find key feedback loops in eco-socio-hydrological systems. Nabong et al. (2022) combined Graph Theory, CLDs, and Cross-Impact Matrices to create a more holistic framework for leverage points identification and analysis. Kellner (2023) introduced the concept of Networks of Action Situations, highlighting how interconnected leverage points can influence broader systemic outcomes. Giordano et al. (2025) proposed a semi-qualitative system behavior analysis for leverage points identification, combining "structural" and "descriptive" analysis of CLDs using Graph Theory metrics and feedback loops analysis.

Despite these developments, important gaps remain in leverage points identification. Leverage points are commonly treated as isolated nodes; however, since they more commonly operate through intricate interdependencies throughout the system (Fischer & Riechers, 2019), their identification becomes highly dependent on the modeler's expertise, especially in large, complex CLDs with numerous feedback loops (Crielaard et al., 2023). Moreover, although semi-qualitative tools such as CLDs and Cross-Impact Matrices are fundamental for identifying potential leverage nodes, they fail to capture the dynamic and uncertain aspects of leverage points as loops and links (Koskimäki, 2021). For these reasons, there is a need to use more structured modeling approaches that capture both the static and dynamic aspects of system behavior and how leverage points work together to create chains of influence, which may result in unforeseen consequences or beneficial synergies in Nexus systems. This approach would reduce the heavy reliance on the modeler's individual interpretation, ensuring that the identification of leverage points is more objective and less prone to biases.

To overcome these gaps, this research combines participatory SD modeling tools (i.e., CLDs and SF models) with other system-analysis methods for the identification and analysis of leverage points. In particular, semi-qualitative approaches (e.g., Centrality Measures and Impact Matrices) are proposed to assess the significance of nodes within systems and their roles (Dablander & Hinne, 2019), while quantitative approaches (e.g., Loops that Matter and stochastic approaches) are used to analyze the dynamic and uncertain nature of leverage points over time and contexts (Amorocho-Daza et al., 2024). This two-pronged approach seeks to offer a deeper insight into leverage points, characterizing them as dynamic, uncertain high-leverage factors and processes (i.e., spots, interconnected links, and feedback loops) rather than only discrete intervention points, thus supporting more precise predictions related to their capacity to alter system behavior.

1.3. Research Aim and Questions

This study proposes a modeling process rooted in non-linear systems thinking with the aim of identifying leverage points for managing cascading impacts in WEF Nexus systems. By integrating SD modeling with other system-analysis tools like Centrality Measures and Impact Matrices, this study identifies key factors, relationships, and loops in Nexus systems. Stochastic methods are employed to account for uncertainty. Furthermore, the adoption of a strongly participatory approach ensures transdisciplinarity (Liu et al., 2018; Pluchinotta, Zhou, Moore, et al., 2024).

Two key research questions guide this research: (a) How can leverage points be identified and quantified to manage cascading impacts in Nexus systems? (b) To what extent does the uncertainty within Nexus systems affect cascading impacts and their management?

The proposed modeling process is applied to the Pinios River Basin (PRB) in central Greece, a case study from the REXUS (Managing Resilient Nexus Systems Through Participatory Systems Dynamics Modeling, https://www.rexusproject.eu/) and LENSES (LEarning and Action Alliances for NexuS EnvironmentS in an Uncertain Future, https://www.lenses-prima.eu/) EU-funded projects. The paper is organized as follows: Section 2 discusses the role of leverage points in Nexus systems, Section 3 outlines the proposed modeling process, and Section 4 presents results from its application to a complex WEF Nexus system.

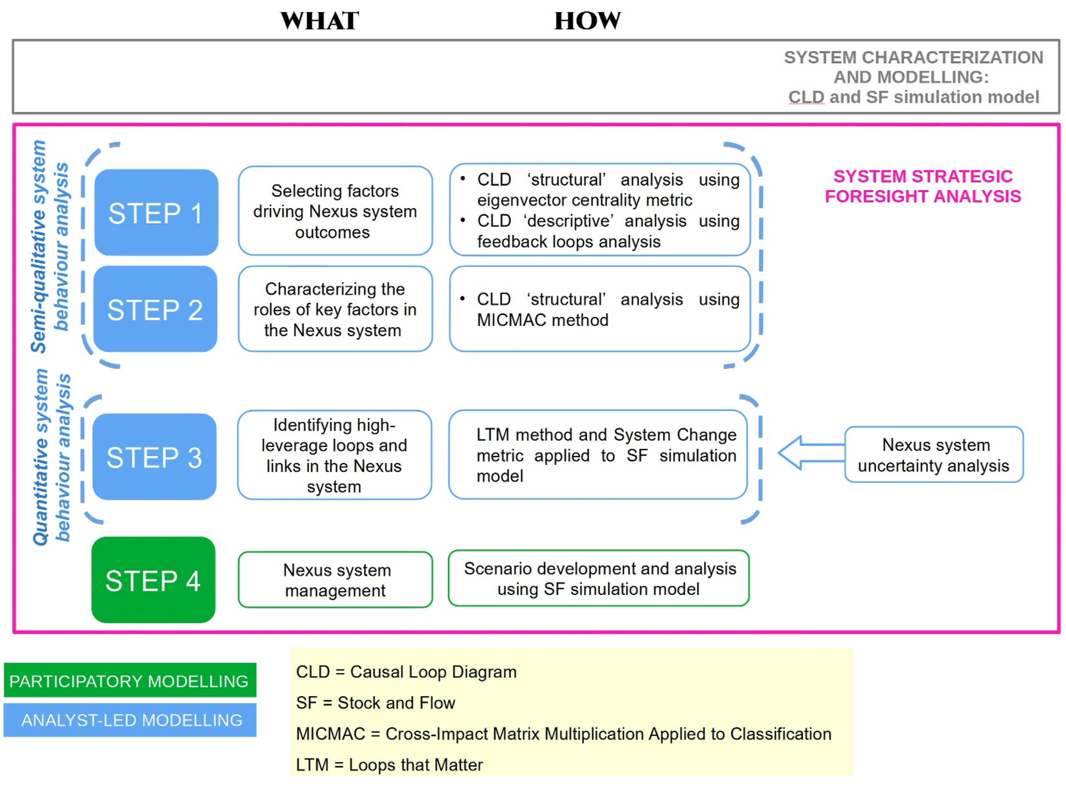

Figure 1. Overview of the proposed modeling process, with a focus on "system strategic foresight analysis."

2. Modeling Process

The proposed modeling process is outlined in Figure 1. It includes modeling phases led by the analyst and participatory modeling phases with stakeholders (shown in blue and green boxes, respectively). The process consists of two main parts: "system characterization and modeling" and "system strategic foresight analysis." The former supports the understanding of the systems' structure and dynamics; the latter identifies leverage points and explores future scenarios to support effective Nexus management. This work focuses on the "system strategic foresight analysis"; however, for the sake of clarity and completeness, a brief overview of the first part of the modeling process is provided afterward.

2.1. System Characterization and Modeling

To map key variables, interactions, and feedback loops within the system, a CLD (i.e., a qualitative SD model) is developed based on existing information about the analyzed system (e.g., reports, existing models, scientific/gray literature, etc) (Zhou et al., 2025). The causal connections are then discussed and revised based on the inputs from local stakeholders in participatory workshops, to ensure that the map reflects their perspectives (see e.g., Coletta, Pagano, Pluchinotta, et al., 2024, Coletta et al., 2021, 2023; Giordano et al., 2025). The work from Malamataris et al. (2025) provides further information on the CLD construction process.

The CLD is then translated into an SF simulation model (i.e., a quantitative SD model) (see e.g., Pagano et al., 2019; Pluchinotta et al., 2021) to analyze system evolution over time. The parameters and equations for the SF model are derived from multiple sources, depending on the "level of intangibility" of the aspects involved and the availability of related equations in the literature (Pluchinotta, Zhou, & Zimmermann, 2024). Specifically, the SF model can handle both physical (hard) and soft (intangible) variables (Coletta, Pagano, Zimmermann, et al., 2024). Physical variables, such as water quality (mg/l), energy consumption (kWh), agricultural productivity (ton/ha), are implemented using either observed data or the results of sectoral models (e.g., hydrological models, economic models, etc). Soft variables, such as sustainability indicators or well-being measures, which are often neglected by traditional modeling approaches to Nexus systems management, are incorporated using dimensionless terms (ranging from 0 to 1) and are linked to other (hard or soft) variables in a way that reflects their dynamic interactions, often based on local stakeholders' or experts' judgment. The work from Pagano et al. (2025) provides full information on the process of SF model construction and analysis.

To ensure that the SF model effectively supports decision-making, it must undergo testing to identify any error that could undermine its reliability and credibility (Barlas, 2025). The SD community identifies two main types of testing: model verification and model validation (Sterman, 2002). Verification includes: (a) ensuring numerical stability by testing the integration method and time step size, (b) checking equations and inputs for errors, and (c) verifying dimensional consistency (Pruyt, 2013). Numerical stability is tested using different integration methods (e.g., Euler, Runge-Kutta) and by evaluating sensitivity to time step variations (e.g., halving the step size) to ensure consistent outputs (Sterman, 2000). Errors in equations and dimensional consistency can be automatically checked in SD software.

Given that SF models are causal-descriptive, validating their internal structure (i.e., relationships among variables) is crucial (Barlas & Carpenter, 1990; Forrester, 1968; Lane, 1995). This involves comparing model equations and structure with available information from stakeholders, experts, and literature, from early modeling stages (Barlas, 1996). Structure-oriented behavior tests, which assign extreme values to parameters and compare model behaviors to hypothesized ones, help identify structural flaws (Barlas, 1989). Once structural validity is confirmed, behavior credibility testing checks whether the model's outputs align with real data, focusing on trend prediction rather than exact point prediction due to the long-term policy focus of SF models. This requires statistical significance testing, though its use in SF models is controversial. Since SF models generate autocorrelated and cross-correlated data, which violate the assumptions necessary for valid statistical tests, applying these tests often necessitates model simplification or data transformation, processes that can be complex and sometimes unsatisfactory (Senge, 1977). Additionally, with multiple output variables, statistical testing poses a multiple-hypothesis problem.

2.2. System Strategic Foresight Analysis

Building on the works of Egerer et al. (2021), Giordano et al. (2025), Kellner (2023), Lam et al. (2021), Murphy and Jones (2020), Nabong et al. (2022), and Videira et al. (2014), the “system strategic foresight analysis” consists of a semi-qualitative and a quantitative phase (see Figure 1). The semi-qualitative phase focuses on both the selection of key factors that drive system outcomes and the characterization of their influence and dependence, both of which are carried out using the CLD. This is to identify potential leverage points. Next, the quantitative phase examines the previously identified leverage points further, analyzing their dynamic behavior within the dominant SD as captured by the SF model. By addressing high-leverage loops and links, this approach shifts the focus from individual nodes to complex interactions, providing deeper insight for system management.

2.2.1. Semi-Qualitative System Behavior Analysis

Step 1 Selecting factors driving the Nexus system outcomes

This step is composed of two interrelated activities on CLDs: “structural” and “descriptive” analysis. The former evaluates the structure and connectivity of the system applying a metric from Graph Theory called eigenvector centrality (Murphy & Jones, 2020). The latter focuses on the identification and understanding of key SD and the evolution of variables, particularly through feedback loops (Murphy & Jones, 2021).

Unlike previous studies (e.g., Lam et al., 2021; Murphy & Jones, 2020), this work uses the eigenvector centrality only, which better captures the systemic importance of nodes by evaluating their connections to other influential nodes, thus avoiding misinterpretations common with metrics like degree or betweenness centrality (Crielaard et al., 2023). Nodes with higher eigenvector centrality scores are those significant in the network because they are connected to many well-connected nodes (Dablander & Hinne, 2019). Details on the mathematical calculation of eigenvector centrality from CLDs can be found in Text S1 in Supporting Information S1.

However, this metric does not consider the presence of feedback loops within CLDs and therefore relying solely on eigenvector centrality may overlook critical drivers of Nexus system outcomes (Bonacich, 2007). To overcome this problem, feedback loops analysis is used in addition to eigenvector centrality. Therefore, those elements with high eigenvector centrality (i.e., the leaders) are examined for how they operate within key feedback loops (Forrester, 1961). Feedback loops within CLDs can drive exponential growths or declines (reinforcing

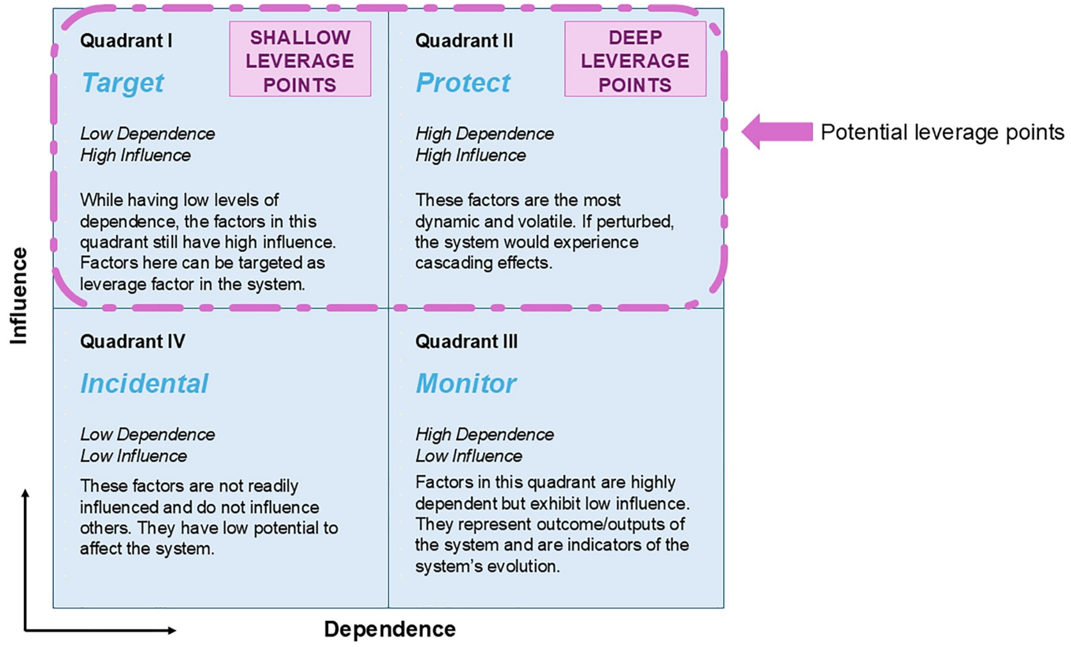

Figure 2. Direct and indirect influence-dependence chart revealing the roles of factors in the Nexus system (adapted from Nabong et al. (2022)).

loops) or promote stability (balancing loops) (Meadows, 2008). The combination of eigenvector centrality and feedback loops analysis can support a more effective identification of leverage points and strategies within Nexus systems.

Step 2 Characterizing the roles of key factors in the Nexus system

Step 2 helps characterize the roles of key factors in Nexus system outcomes. In particular, potential leverage points are here identified in order to guide decision-making. Using the MICMAC method (Cross-Impact Matrix Multiplication Applied to Classification), an Impact Matrix is generated from the CLD. In spite of its many applications in complex system analysis (see e.g., Corral-Quintana et al., 2016; Dhirasasna et al., 2021), MICMAC has more recently been used for Integrated Water Resources Management and WEF Nexus systems management (Manzano-Solís et al., 2019; Nabong et al., 2022; Valcourt et al., 2020; Walters et al., 2022). To determine the role of key factors within the system, this method evaluates their mutual direct and indirect relationships (due to e.g., feedback loops) classifying their influence (i.e., their cumulative impact) and dependence (i.e., their susceptibility to other factors) (Delgado-Serrano et al., 2016). Based on this information, an influence-dependence graph is generated. This chart categorizes the key factors identified in Step 1 into four different roles (see Figure 2), thus offering a practical tool to decision-makers:

- Target factors (Quadrant I): High influence, low dependence. These factors represent shallow leverage points, where changes are easy to implement but generate only incremental improvements within the system (Fischer & Riechers, 2019).
- Protect factors (Quadrant II): High influence, high dependence. These factors are deep leverage points, difficult to change but drivers of transformations within the system (Patterson et al., 2017).
- Monitor factors (Quadrant III): High dependence, low influence. These factors are system outcomes that require monitoring to anticipate shifts at the system level.
- Incidental factors (Quadrant IV): Low influence, low dependence. These are not relevant to policy-making and therefore are excluded from the analysis.

In this way, MICMAC analysis helps identify leverage points and support decision-makers in the effective management of cascading impacts in Nexus systems. Details on the mathematical process behind the MICMAC method can be found in Text S2 in Supporting Information S1.

2.2.2. Quantitative System Behavior Analysis

Step 3 Identifying high-leverage loops and links in the Nexus system

Quantitative system behavior analysis (Figure 1) enhances understanding of leverage points through the identification of high-leverage loops and links within the system's dominant dynamics, as represented by the SF simulation model. This phase, differently from the semi-qualitative phase, which considers leverage points as nodes, examines them as dynamic links and feedback loops. This provides a holistic view of their role in influencing system outcomes, thus guiding interventions to optimize results and mitigate cascading impacts.

The identification of dominant links and feedback loops over time is achieved through the use of the Loops That Matter (LTM) method, integrated into Stella Architect, an SD modeling software (Schoenberg, 2020). Metrics like link score, loop score, and relative loop score enable LTM to highlight the most influential links and loops, specifying also their polarity and contribution to SD (Schoenberg et al., 2020). Specifically, link score quantifies a causal link's contribution and polarity; loop score aggregates link contributions within a feedback loop; relative loop score normalizes loop scores to identify dominant loops over time. LTM helps decision-makers in (a) understanding when and where significant changes occur at the system level and consequently in (b) prioritizing interventions (Aboah & Enahoro, 2022). LTM is complemented with the System Change metric (Schoenberg et al., 2023) which measures aggregate state changes across the system and therefore highlights critical periods of flux. Together, these metrics identify impactful leverage loops and links during system transitions, supporting effective Nexus management. For mathematical details on LTM and the System Change metric, refer to Text S3 in Supporting Information S1.

2.2.3. Nexus System Uncertainty Analysis

Aleatory uncertainty should be carefully addressed in modeling (Beven, 2009; Montanari, 2007). This means that randomness must be incorporated into model inputs and/or internal processes using ranges of variation and probability distributions to represent uncertain factors (Morgan & Henrion, 1990). In this way, uncertainty propagation through the system can be analyzed, thus highlighting critical outcomes (Beven, 2016; Montanari, 2011; Montanari & Koutsoyiannis, 2012). For this purpose, Monte Carlo sensitivity analysis is often used. This method systematically simulates a wide range of outcomes, accounting for randomness in inputs, processes, or both (Pruyt, 2013). While SF models are traditionally deterministic (Susnik et al., 2012), stochastic methods have become essential for analyzing WEF Nexus systems under uncertainties such as climate change, population growth, and economic fluctuations (Amorocho-Daza et al., 2024; Mereu et al., 2016; Sušnik et al., 2018, 2021). Uncertainty Analysis (UA) in SD modeling, supported by Monte Carlo methods, provides valuable insights into system behavior without altering the model structure (Hekimoğlu & Barlas, 2010). The steps of UA in SD modeling are detailed in the following.

Step 1 of the UA: Assigning ranges and distributions to fluctuating factors

The first step in UA introduces uncertainty into the Nexus system by assigning ranges and probability distributions to hydrological, social, and environmental parameters (or variables) subject to inherent fluctuations. Typically, parameter ranges are established at ±20% of their value, based on actual system data (Sterman, 2000). However, it is important to avoid "overconfidence", as experts may underestimate potential values. Therefore, factors that might be directly affected by hydrological extreme events, such as river flow, require wider intervals (e.g., ±100% of their value) to account for exceptional conditions, while other factors with more stable or well-understood behavior might only require smaller intervals (e.g., ±50%) to reflect typical, physically plausible fluctuations. An exception is made for aspects with standardized or regulated ranges, such as fertilizer application rates, where ranges are set according to official guidelines.

The choice of probability distributions depends on data availability (Ford, 1990). If data are available, distributions are fitted to the data set. Historical data may be adjusted to reflect projected trends over time (e.g., demographic shifts, resource fluctuations), and the parameters of various distributions can be estimated using statistical and computational tools. These tools help to select the most appropriate distribution for the data, such as Weibull, Normal, Gamma, or Exponential, depending on the nature of the variable and its expected behavior. In cases where no data are available, distributions are selected based on typical use cases. For example, the Uniform distribution is used when every value within a specified range has an equal chance of occurring, making it ideal for situations where there is limited information about the behavior of a variable. On the other hand, the

Triangular distribution is more suitable when estimates for the minimum, maximum, and most likely values are available, which is often the case in scenarios involving uncertain demand or resource availability (Ford, 1999).

Step 2 of the UA: Selecting a sampling strategy

The second step in UA involves choosing a sampling strategy, which can be either random or structured. Random sampling can be univariate (i.e., one parameter is altered at a time) and multivariate (i.e., multiple parameters are changed at once) (Saltelli, 2002). Structured sampling methods, for example, Latin Hypercube (stratified sampling) and Latin Grid (systematic grid search), ensure more even coverage of the parameter space (McKay et al., 1976). For complex models, choosing multivariate or structured sampling is preferred because it better captures the interactions between parameters and variables, and it enables more comprehensive analysis (Ford & Flynn, 2005).

Step 3 of the UA: Making sensitivity simulations

The third step in UA focuses on running sensitivity simulations in order to evaluate the response of the system to changes in parameters (or variables). To do that, seed values and the number of simulations have to be determined. The seed values influence the sequence of random numbers: a fixed seed ensures reproducibility (useful for debugging or scenario demonstrations) while a random seed promotes broader exploration. Random seeds are generally preferred in UA. Nevertheless, repeating analyses with different fixed seeds can provide additional insights. Besides that, too few simulations may miss important variability. However, a greater number of simulations may improve accuracy, albeit with diminishing returns (Hekimoğlu & Barlas, 2010). Typically, 200 simulations (the default setting in various SF modeling software) provide a balanced approach, allowing for robust exploration of the parameter space while remaining computationally efficient.

Step 4 of the UA: Exploring possible behaviors

The fourth step in UA involves the exploration of the system's possible behaviors. In SD modeling, behavior patterns over time are often more significant than exact numerical values, with emphasis on trends rather than specific points/events (Sterman, 2000). Sensitivity analysis examines how these patterns shift with changes in model structure or parameter values. The width of uncertainty bands serves as an empirical proxy for model sensitivity: narrow bands indicate that the system's behavior remains relatively stable even when parameters fluctuate across their defined ranges (i.e., low sensitivity); wider bands suggest that the system's outputs are more responsive to those variations (i.e., high sensitivity). This study introduces system-wide behavior sensitivity, which can evaluate how fluctuations in parameters influence overall system behavior and evolving interactions among variables, including high-leverage loops and links. This is especially crucial when it comes to complex Nexus systems, in which both small changes and dynamic shifts in input can produce significant, non-linear effects and cascading impacts due to interdependencies and feedback loops (Ford, 1999).

2.2.4. Nexus System Management

This phase focuses on the design and testing of interventions to orient Nexus systems toward sustainability. High-leverage nodes, links and loops, previous identified, function as sensitive points and processes for impactful, system-wide changes (Sterman, 2000). Therefore, if a leverage point is water availability for irrigation and a key issue for the system is the depletion of groundwater resources due to inefficient irrigation practices, interventions should focus on improving water use efficiency and adopting sustainable irrigation methods. If, however, water availability for irrigation is not identified as a leverage point in this system, actions targeting water use efficiency may not lead to significant improvements in groundwater conservation. In this case, the sensitive point may lie elsewhere, such as improving soil health to reduce water loss through evaporation or increasing crop resilience to drought conditions. Stakeholders are crucial to co-design effective interventions, which can also support defining long-term goals across Nexus sectors and selecting measures from a variety of predefined and newly proposes solutions to target leverage points.

Scenario analysis explores intervention-driven futures by addressing "what if" and "which is best" questions (Malbon & Parkhurst, 2022). Through the simulation of a wide array of scenarios under varying conditions, the SF model can evaluate the effectiveness of a given intervention. Stakeholder feedback can validate scenario results further, ensuring interventions are practical and account for system complexities. This iterative process supports sustainable and impactful decision-making (Crausbay et al., 2022).

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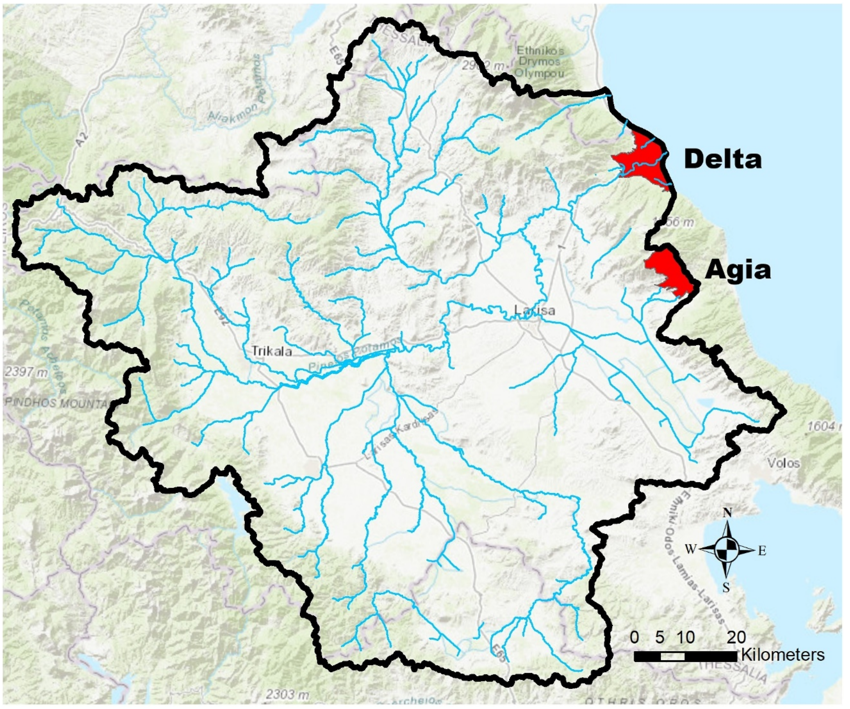

Figure 3. Pinios river basin in Greece.

3. Application of the Modeling Process to the Pinios River Basin

3.1. The Pinios River Basin From the WEF Nexus Perspective

The proposed modeling process is applied to the PRB (Figure 3), a key agricultural region in central Greece (around 11,000 km^2). Agricultural activities use over 90% of water resources, both from groundwater and surface water. Poor water management has caused groundwater over-abstraction, which has led to water scarcity, environmental degradation, and high nitrate levels.

This study focuses on two areas of the PRB that present major WEF Nexus challenges, namely the Agia Watershed and the Pinios River Delta (PRD). The Agia Watershed (53 km^2), in the southern PRB, is dominated by fruit orchards (e.g., apples, cherries, and chestnuts) and irrigation depends mainly on private groundwater wells, thus leading to shortages during peak seasons and droughts. Poor practices have caused groundwater contamination due to nitrates and salinization and consequent disruptions to natural water supplies, affecting ecosystems and wildlife health (Pisinaras et al., 2018). Water management improvement is essential to balance agriculture with ecosystem preservation.

The PRD (75 km^2), located at the basin's downstream end, is protected under NATURA 2000 and supports agriculture and tourism. Water-intensive crops (e.g., corn, wheat, and sunflower) are produced (Pisinaras et al., 2021). Surface water from the Pinios River is the main irrigation source, but groundwater is vital during dry periods. Tourism and agricultural expansion have led to water overuse, which has caused salinization, habitat loss, and biodiversity threats. Balancing water needs with ecosystem health is critical for sustainability.

Climate change impacts are increasing the stress on water resources, thus exacerbating the issues in both Agia and PRD (Loukas, 2010). For this reason, a WEF Nexus approach is essential to promote water conservation, sustainable agriculture, and ecosystem protection, ensuring the basin's long-term resilience.

3.2. Results

This section presents the results of applying the proposed modeling process to the PRB. Figure 4 presents the final CLD for the PRB, co-designed with stakeholders during participatory activities. The map highlights the strong

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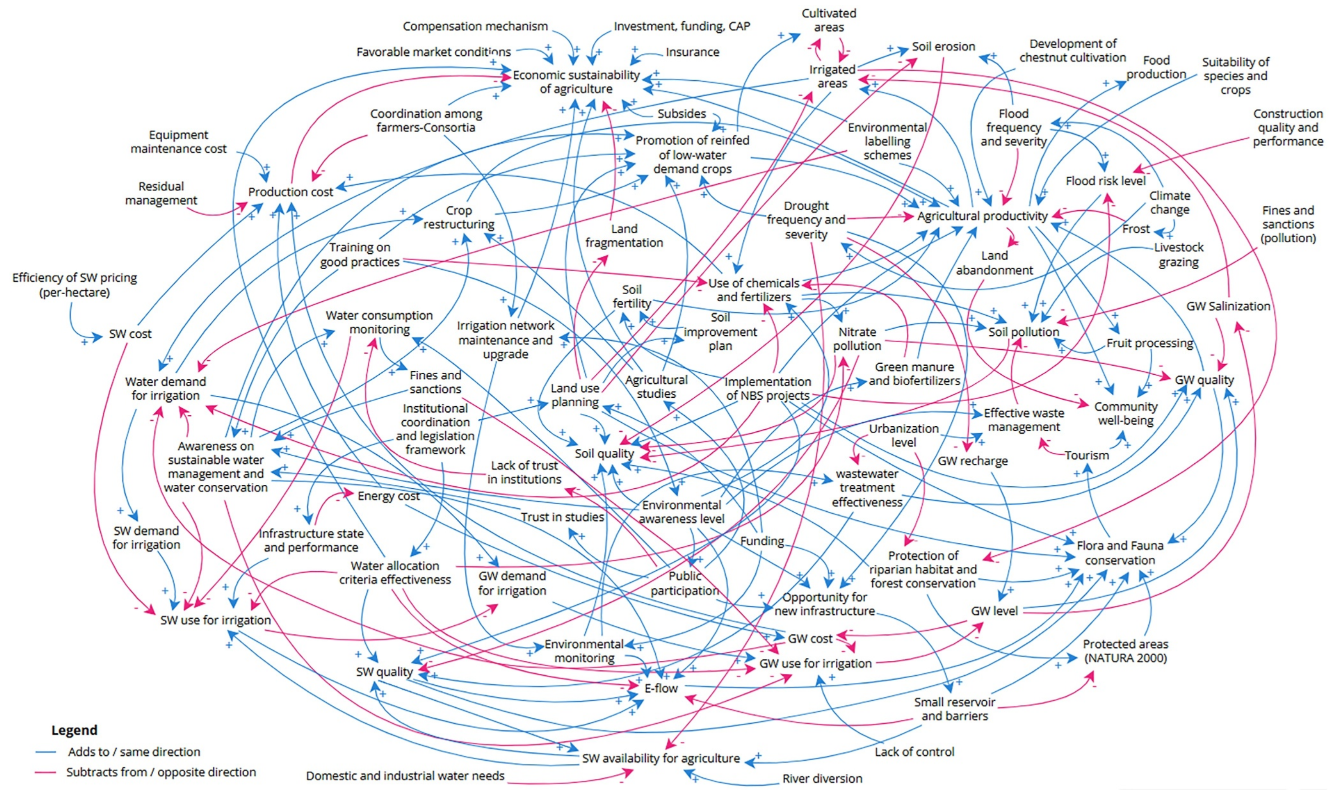

Figure 4. Causal Loop Diagram developed for the Pinios River Basin. Pink arrows indicate negative links, while blue arrows indicate positive links. GW refers to groundwater, SW to surface water, and NBS to Nature Based Solutions.

interconnectedness across WEF Nexus sectors. A detailed narrative of the CLD structure is beyond the scope of this work. Further details on PRB conceptualization and mapping are in Malamataris et al. (2025).

3.2.1. Identifying Key Factors and Roles in the Pinios River Basin

The CLD in Figure 4 was analyzed using eigenvector centrality via Kumu's Social Network Analysis module (www.kumu.io). Table 1 lists the top 10 variables with the highest eigenvector centrality, that is, the leaders for the PRB. Results highlight the influence of "Community well-being" (0.081) and "Soil quality" (0.079) in driving system outcomes, alongside "Flora and fauna conservation" (0.058) and "Soil pollution" (0.057), which are crucial for environmental and social health. The importance of agriculture and water management in the area is confirmed by the high scores of "Irrigated areas" (0.053) and "Agricultural productivity" (0.050).

To have a more precise idea of the variables driving PRB outcomes, the "structural" analysis using eigenvector centrality was combined with a "descriptive" feedback loop analysis. The latter reveals that for example, in the "Irrigated agriculture" balancing feedback loop (Figure 5), increased productivity may drive irrigation expansion, leading to higher "Use of chemicals and fertilizers" and contributing to "Nitrate pollution" and reduced "groundwater (GW) quality." This decline in "GW quality" might limit productivity, completing the balancing loop. This loop highlights that, despite their low eigenvector centrality scores, "GW quality", "Nitrate pollution" and "Use of chemicals and fertilizers" are key variables in the PRB dynamics. In fact, acting on them can sustain productivity while minimizing environmental impacts. Additional key factors influencing PRB outcomes are listed in the third column of Table 1.

The MICMAC method was then automatically applied to all key factors driving system outcomes using Kumu's Social Network Analysis module (www.kumu.io). Dependence and influence scores were calculated (see Text S4 in Supporting Information S1 for details) and then projected onto a two-dimensional chart to classify factors as target, protect, monitor, or incidental. The resulting chart is shown in Figure 6.

Table 1
Results of the Semi-Qualitative System Behavior Analysis for the Pinios River Basin

System leaders	Eigenvector centrality scores	Other key factors involved in feedback loops
Community well-being	0.081	• Use of chemicals and fertilizers
Soil quality	0.079	• Nitrate pollution
Flora and fauna conservation	0.058	• GW (groundwater) quality
Soil pollution	0.057	• GW demand for irrigation
Irrigated areas	0.053	• GW use for irrigation
Agricultural productivity	0.050	• GW level
Economic sustainability of agriculture	0.042	• GW salinization
Cultivated areas	0.038	• SW (surface water) demand for irrigation
Water demand for irrigation	0.036	• SW use for irrigation
Tourism	0.033	• SW quality
		• SW availability for agriculture
		• GW cost

Note. The first two columns display eigenvector centrality values (0–1) from the "structural" analysis of the Causal Loop Diagram (CLD), while the third column shows outcomes from the "descriptive" analysis of the CLD.

The MICMAC analysis revealed that factors in the upper-right quadrant of the chart (e.g., "Water demand for irrigation" (1, 1), "GW demand for irrigation" (0.783, 0.626), and "Cultivated areas" (0.672, 0.881)), are deep leverage points, which, if perturbed, may generate cascading impacts across the PRB. This dominance of deep leverage points may depend on the variables chosen for the analysis and the strong interconnections and dependencies between them. "GW demand for irrigation" has high dependence (0.783), making it vulnerable to changes in other factors, despite its lower influence (0.626). "Cultivated areas" is less dependent (0.672) but highly influential (0.881) and therefore capable of driving changes at the system level. "Water demand for irrigation" has a central role and potential for broad effects because of the highest influence and dependence (1, 1). Monitoring variables include "Flora and fauna conservation" (0.647, 0) and "Economic sustainability of agriculture" (0.964, 0). While these factors lack direct influence (i.e., the influence is zero), they are highly sensitive to system changes, making them critical for observation and evaluation.

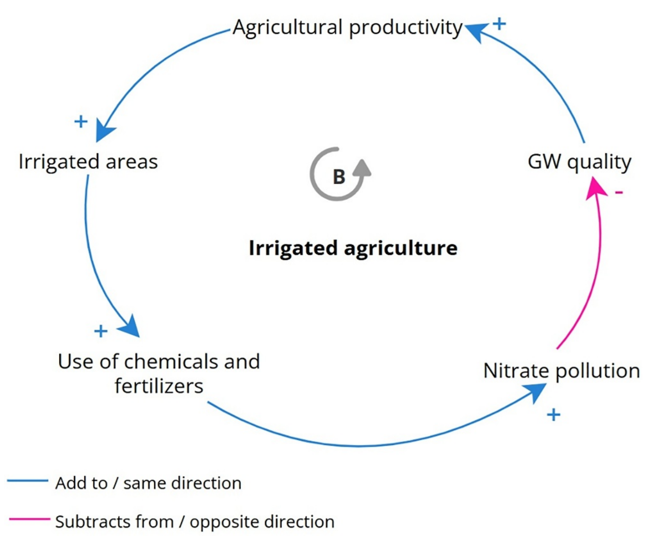

Figure 5. "Irrigated agriculture" feedback loop in the Pinios Causal Loop Diagram. The pink arrows represent negative links, while the blue arrows represent positive links. GW refers to groundwater.

3.2.2. Leverage Points and Cascading Impacts Under Uncertainty

While the CLD focused on key leverage nodes within the PRB system, the quantitative SF model was used to identify high-leverage loops and links. The SF model simulated a 30-year period with a monthly time step, chosen to capture key system changes (e.g., impacts of climate change and shifts in agriculture) in sufficient detail while maintaining a balance between information quality and computational efficiency. A comprehensive description of the SF model is beyond the scope of this paper; for detailed information on the PRB simulation model, please refer to Pagano et al. (2025). The SF model was tested for consistency in terms of equations, inputs, and units. In addition, an extensive series of simulations were run using different integration methods (i.e., Euler, fourth-order Runge-Kutta with both automatic and fixed step size adjustments, and second-order Runge-Kutta with both automatic and fixed step size). None of these tests revealed signs of numerical instability. Based on these results, the Euler method was selected for model analysis due to its computational efficiency (Forrester, 1961). Numerical stability was also confirmed by halving the time step.

The PRB SF model was validated by comparing causal relationships and equations with input from participatory workshops with stakeholders, meetings with experts, and gray literature. Extreme values were assigned to some parameters based on "feared conditions" expressed by local stakeholders, and the model behaved as expected. Since real data for key outputs (e.g., "Potential for agrotourism," "State of natural areas," "Average agricultural

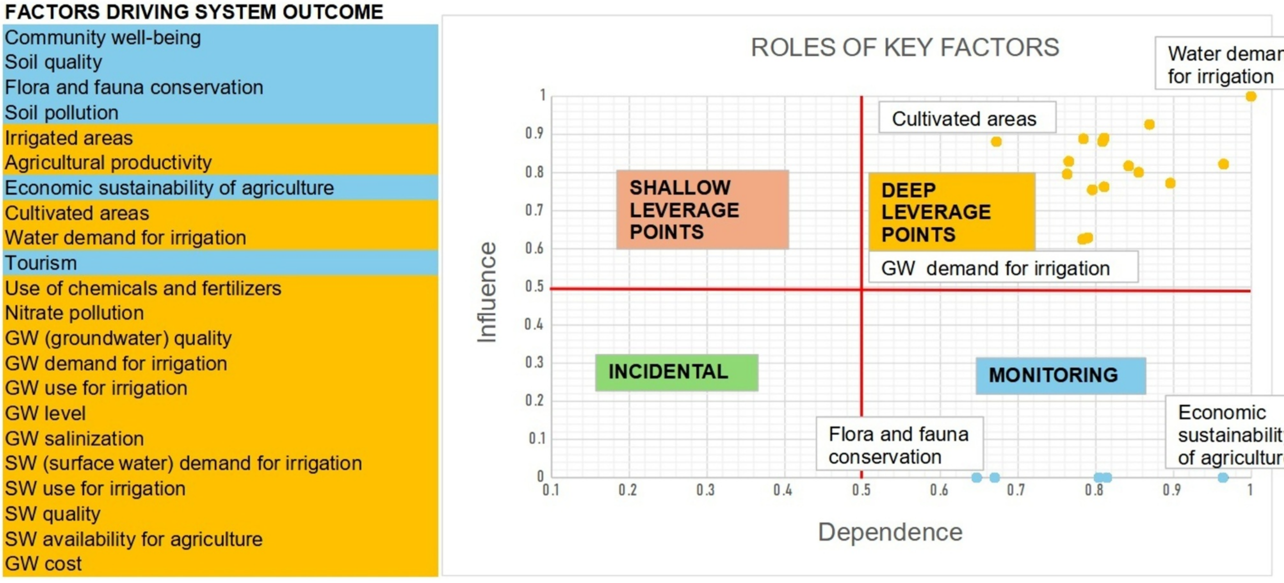

Figure 6. Roles of key factors in the Pinios River Basin.

sustainability") were unavailable, behavior credibility was tested through stakeholders' and pilot leaders' feedback on key output behaviors. The list of variables and mathematical equations behind the SF model are included in the Text S5 in Supporting Information S1.

To account for uncertainty in the SF model of the PRB, ranges and probability distributions were assigned to inherently random parameters (or variables), such as "Average Pinios river flow", "Potential contribution of capillary rise", "Population" and "Average crop unit water need." Text S6 in Supporting Information S1 summarizes, for each parameter and variable, the actual value of the model, the ranges, the distribution, and the rationale behind that choice. Then, multivariate random sampling was chosen, and 200 sensitivity simulations were run with a random seed. The main results of this system-wide behavior sensitivity are summarized below. For brevity, the results focus on one high-leverage loop, one link, and one monitoring variable, selected based on how frequently it was mentioned by stakeholders as critical factor influencing the system.

Using Stella Architect's "calculate loop dominance information" function, dominant Loop Sets were identified in the SF model. These sets were analyzed selecting the time periods where system changes were most significant and calculating the relative loop scores within these periods. Simulations revealed that the presence and influence of high-leverage loops can vary from one simulation to another, sometimes resulting in additional loops, fewer loops, or entirely different loops compared to deterministic modeling. Therefore, a loop may emerge as highly leveraged in some runs but not in others. This variability emphasizes the inherent randomness of the dynamics affecting PRB stability and highlights the potential for cascading impacts. Furthermore, the periods of dominance and the percentage contributions of high leverage loops to system behavior may vary between different simulations. This means that even when a loop remains high-leverage across simulations, its timing and strength of influence may vary. For example, the "SNA (State of Natural Areas) decrease" loop, which in deterministic modeling dominates between months 120 and 270 with a relative loop score of approximately 57% (see Figure 7a), may, in a run of the stochastic model, affect the system across different time windows over the 360-month period, sometimes exceeding the 57% score during certain intervals (see Figure 7b).

Simulations showed significant variability both in the occurrence and influence of high-leverage links across runs. Some links (e.g., the relationship between "Average water quality" and "SNA (State of Natural Areas) decrease rate") may be low-leverage in certain simulations (relative score below 50%, Figure 8a) but high-leverage in others during specific time windows (Figure 8b). This dynamic behavior underscores the sensitivity of PRB system interactions to random perturbations.

As far as the monitoring variables, for the sake of brevity, only one of them is displayed below in dimensionless units, ranging from 0 (low) to 1 (high). Although the stochastic outcome of "Average agricultural sustainability"

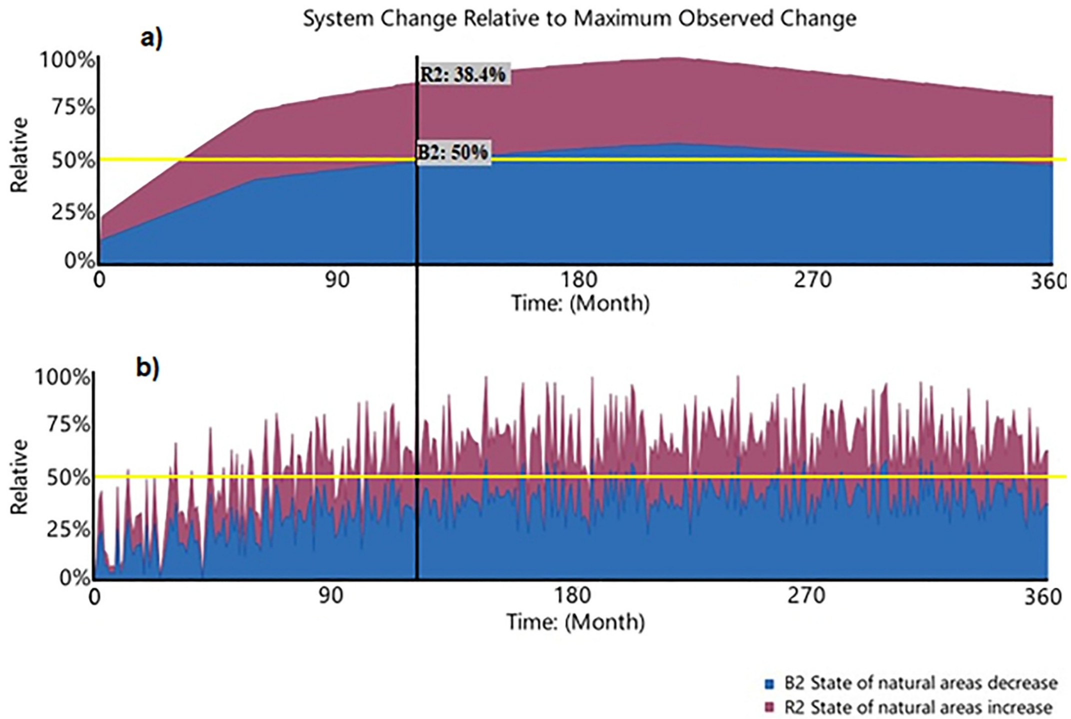

Figure 7. Contribution to system change plot by the Loop Set "State of natural areas (SNA)" in (a) deterministic modeling and (b) stochastic modeling. The R2 loop (SNA increase) illustrates how positive changes in land use planning can lead to an increase in the state of natural areas, fostering their recovery and expansion. On the other hand, the B2 loop (SNA decrease) represents the pressures that lead to a decline in natural areas, such as urban expansion and the conversion of land for agriculture. These loops emphasize the reinforcing and balancing processes that affect the sustainability of natural areas within the area.

(gray area in Figure 9) showed slightly more variability compared to the baseline/deterministic (red line), both behaviors follow a similar downward trend over the 360-month period in the PRB regions. This pattern, consistent also among other monitoring variables, indicates that despite parameter sensitivity, the overall system behavior remains robust. The relatively narrow uncertainty bands around output variables further suggest low to moderate sensitivity of the model to the selected parameter ranges, confirming that the system maintains consistent trends across simulations even as individual parameters vary within plausible limits.

Table 2 lists the leverage points identified for the PRB through the semi-quantitative analysis of the CLD and the quantitative analysis of the SF model. The leverage points are classified into nodes (leverage points), loops (high-leverage loops) and links (high-leverage links). For clarity, only the most recurrent links and loops across simulations are included. Variables are listed as they appear in the SF model, with broader concepts (e.g., "State of natural areas" including "Flora and fauna conservation" from the CLD) used where applicable.

3.2.3. Cascading Impacts Mitigation in the Pinios River Basin

The high-leverage nodes, links, and loops identified earlier were used as sensitive points for interventions with impact at the system level. Scenario analysis was conducted in collaboration with pilot leaders during an online meeting and incorporated stakeholder insights, thus addressing their needs. Table 3 outlines the scenarios, designed to implement measures targeting the selected leverage points.

Figure 10 shows the behavior of "Average agricultural sustainability" over time for each scenario implemented at the selected leverage points, with the baseline stochastic condition as a reference. Scenarios S3 and S5, which implement socio-institutional and infrastructural measures, produce the most positive cascading impacts. In contrast, measures such as mulching (S1) and optimizing irrigation scheduling (S2) produce more limited improvements. Other monitoring variables such as "Soil quality", "State of natural areas" and "Potential for agrotourism" show similar trends, but are omitted for brevity. Among all scenarios, S3—focusing on socio-

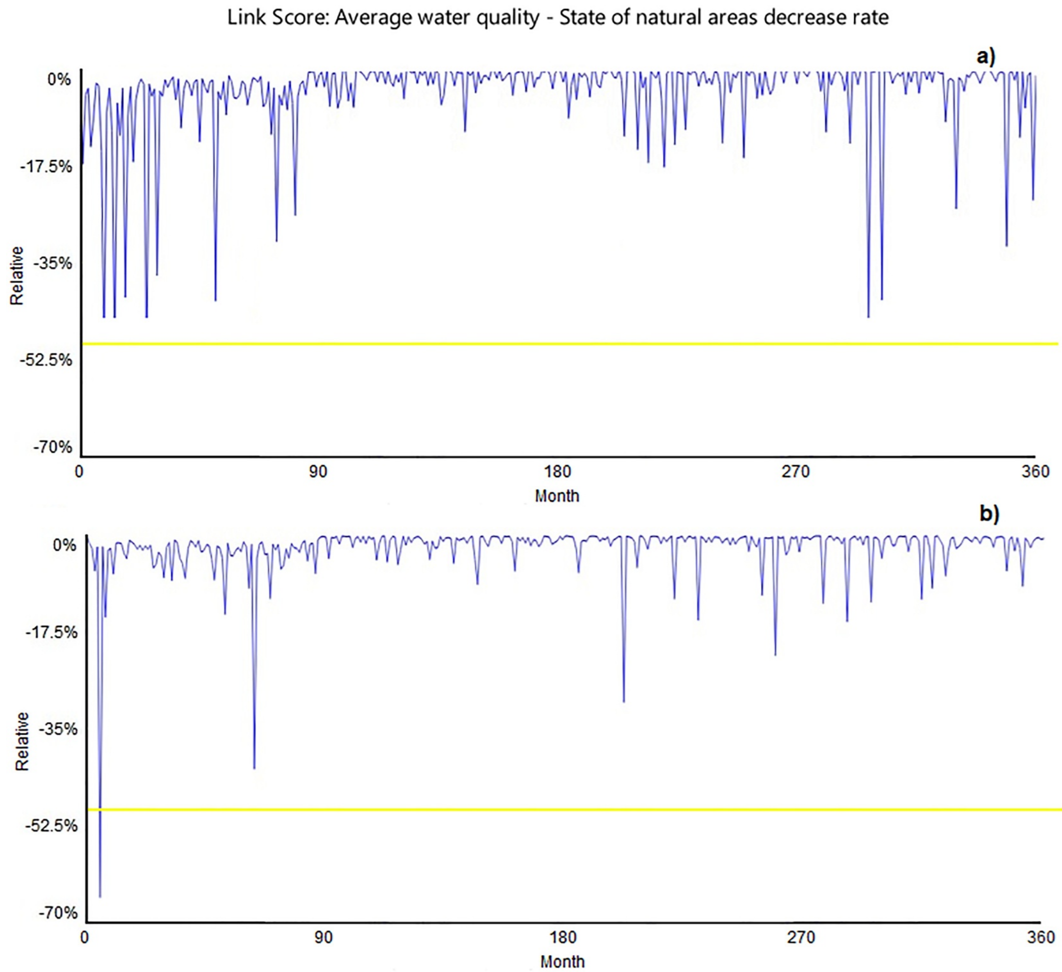

Figure 8. Relative score of the link between "Average water quality" and "State of natural areas (SNA) decrease rate" in two different simulations. Negative values of the relative link scores indicate that the link is inverse.

institutional measures like "farmers' training and awareness" and "land-use planning regulations/actions"—has the most significant positive impact, underscoring the importance of socio-institutional interventions in the PRB.

4. Discussion

This section discusses to what extent the proposed modeling process addresses the key challenges of Nexus systems management (i.e., complexity, non-linearity and uncertainty), while answering the research questions in Section 1.

4.1. Identifying and Quantifying Leverage Points in Nexus Systems

Identifying leverage points in complex systems is a key challenge in Nexus research. This challenge is also echoed in socio-hydrology, which has traditionally focused on understanding co-evolving water-society feedbacks, though often without explicitly identifying leverage points for intervention.

Many studies use only semi-qualitative methods, such as Graph Theory metrics on CLDs, to select leverage points. However, this implies that the dynamic and uncertain nature of leverage points is neglected, and they are oversimplified as fixed nodes (e.g., Murphy & Jones, 2020; Videira et al., 2014). Relying solely on these methods places significant dependence on the modeler's expertise to interpret the system and identify leverage points, especially in large, complex CLDs with numerous feedback loops. This can introduce biases and affect the robustness of the results. To solve this problem, this paper proposed a more structured modeling process that

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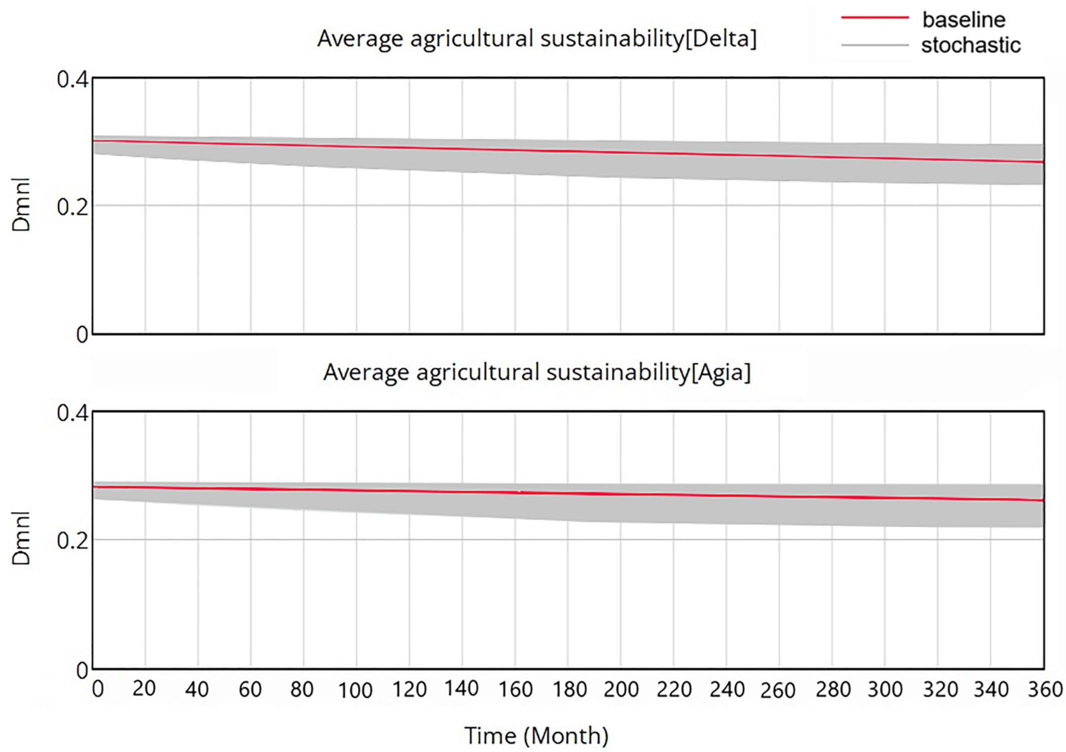

Figure 9. Stochastic (gray area) and baseline (red line) simulations for "Average agricultural sustainability" in Pinios River Delta and Agia. It is displayed in dimensionless units (Dmnl), ranging from 0 (low) to 1 (high).

combined semi-qualitative and quantitative methods based on SD modeling to more effectively identify leverage points in Nexus systems. Stochastic methods were also included to account for uncertainty. This responds to recent calls in socio-hydrology to move beyond descriptive modeling of coupled human-water systems and toward tools that can support transformative action under uncertainty (Razavi et al., 2025).

Using eigenvector centrality on the CLD, the modeling process identified the variables that act as leaders in the system based on their structural importance. Unlike other Graph Theory metrics (e.g., degree centrality, betweenness centrality and closeness centrality), eigenvector centrality avoided false inferences and highlighted variables that influence not only direct connections but also larger networks of highly connected nodes (Crielaard et al., 2023). The analysis of feedback loops completed this structural phase of the modeling approach. It revealed the dynamic roles of these variables within the reinforcing and balancing loops, thus ensuring that key system factors were not overlooked. For instance, in the PRB WEF Nexus system, "GW (groundwater) quality", despite its low structural centrality, emerged as pivotal in balancing loops regulating "Agricultural productivity" and environmental health. The combination of eigenvector centrality and feedback loop analysis helped identify factors that are structurally important and dynamically critical, thus addressing the complexity of the WEF Nexus systems. This finding aligns with socio-hydrological insights on the importance of indirect and often underappreciated feedbacks between environmental quality and social outcomes.

MICMAC analysis on CLD added depth to the modeling process by grouping variables into "target", "protect", "monitor" and "incidental" categories, based on their direct and indirect influence and dependence within the Nexus system. This classification helped to prioritize variables that drive cascading impacts, distinguishing "deep" leverage points, that is, highly influential and dependent variables that are difficult to manage but transformative, from "shallow" leverage points, which are easier to address but have more incremental effects. In the PRB, "Water demand for irrigation", "Agricultural productivity", "GW (groundwater) quality" were identified as deep leverage points and therefore as key drivers of cascading impacts with significant transformative potential. Factors such as "Flora and fauna conservation" and "Economic sustainability of agriculture" were

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Table 2
List of Leverage Points Identified for the Pinios River Basin, Organized Into Nodes, Loops, and Links

Leverage points
Agricultural areas
Agricultural productivity
Irrigation unit water demand
Fertilizers application rate
N (Nitrate) load
GW (groundwater) quality
GW demand
GW use - irrigation
GW availability
High salinity area ratio
SW (surface water) use - irrigation
SW quality
SW availability
Cost of water
HIGH-LEVERAGE LOOPS
Loop B1 [Delta] "GW (groundwater) availability increase"
Loop B2 [Delta] "State of natural areas (SNA) decrease"
Loop B3 [Delta] "Soil quality decrease"
Loop B4 [Agia] "SNA decrease"
Loop B5 [Agia] "Soil quality decrease"
Loop B6 [Delta] "SW (surface water) quality decrease"
Loop B7 [Agia] "SW quality decrease"
HIGH-LEVERAGE LINKS
SW (surface water) quality → Average water quality
SW availability → Water availability for irrigation
State of natural areas (SNA) → Potential for agrotourism
State of riparian habitat and forest conservation (PHF) decrease rate → PHF
Average water quality → PHF decrease rate
Average water quality → SNA decrease rate
Soil quality → Agricultural productivity
Agricultural productivity → Agricultural sustainability
Agricultural productivity → Agricultural profitability (AP) increase rate
AP decrease rate → AP
Cost of water → Production cost
Impact of energy cost on water cost → Cost of water
GW (groundwater) availability → Impact of energy cost on water cost
SW quality → Desertification risk of agricultural areas
Frequency and intensity of extremes → Desertification risk of agricultural areas
Frequency and intensity of extremes → AP decrease rate
Production cost → Agricultural sustainability

Table 3
Scenarios, Their Descriptions, and the Associated Leverage Points for Managing the Pinios River Basin

Scenario	Description	Leverage points affected
Scenario 1 (S1)	Implementation of mulching in 100% of apple orchards (Agia) and kiwi orchards (Delta), reducing irrigation water consumption by 1.02% and 4.93%, respectively, while enhancing soil organic matter.	• N (Nitrate) load
Scenario 2 (S2)	Optimization of irrigation scheduling in 100% of apple orchards (Agia) and kiwi orchards (Delta), achieving water savings of 22.48% and 17.62% without affecting crop yields.	• Cost of water • Cost of water →Production cost
Scenario 3 (S3)	Activation of socio-institutional strategies, including improved farmer training, development of farmers' consortia, and land use planning/regulation actions.	• Agricultural productivity • Agricultural productivity →Agricultural sustainability • Agricultural productivity →Agricultural profitability (AP) increase rate • Production cost →Agricultural sustainability • Fertilizers application rate • Irrigation unit water demand
Scenario 4 (S4)	Creation of new reservoirs for storing surface water to enhance water availability.	• SW availability • SW availability →Water availability for irrigation
Scenario 5 (S5)	Enhancement of irrigation system efficiency to improve water use and reduce wastage.	• Cost of water • Cost of water →Production cost

Note. The leverage points highlight key factors in the system that interventions aim to target for achieving system-wide sustainability.

identified as monitoring variables, meaning they are highly sensitive to changes but less suitable as direct intervention points.

Quantitative analysis using SF modeling and the LTM method improved this understanding because it treated leverage points as dynamic and context-dependent entities. Specifically, LTM identified high-leverage loops and links that dominate system behavior over time, thus addressing the non-linearity of Nexus systems (Schoenberg et al., 2020). For example, in the PRB, the loop "State of natural areas (SNA) decrease" and the link between "Average water quality" and "SNA decrease rate" emerged as key during significant system changes, though their

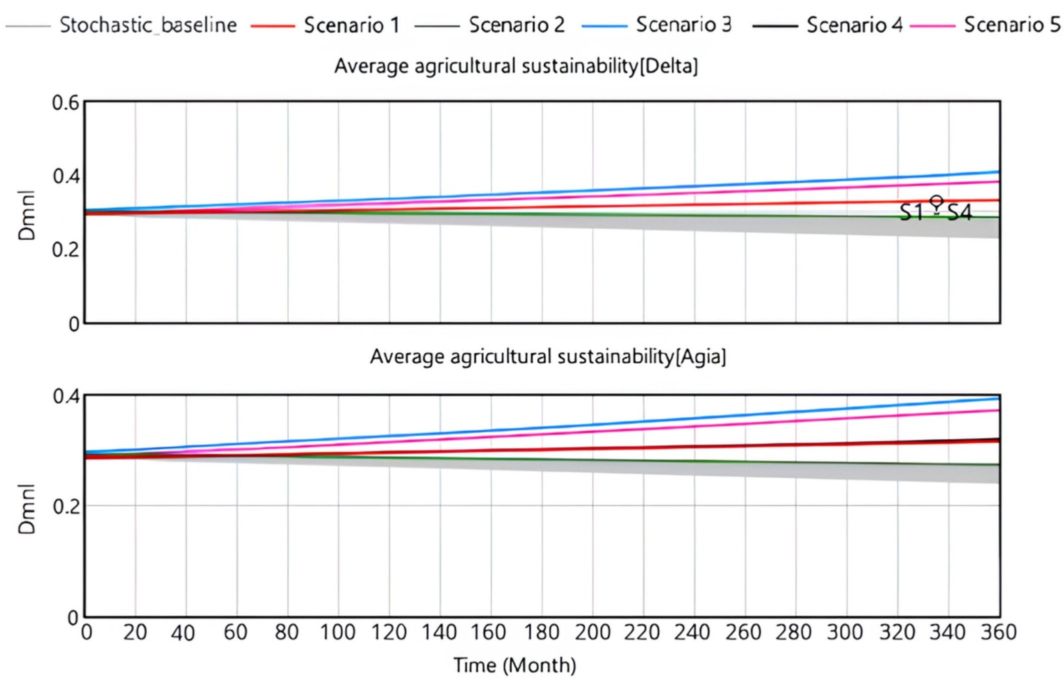

Figure 10. "Average agricultural sustainability" in Pinios River Delta and Agia under scenarios S1–S5.

influence varied temporally. This temporal insight is crucial for adaptive strategies, bridging a key gap in Nexus research (Koskimäki, 2021).

Furthermore, the quantitative analysis addressed the challenge posed by deep leverage nodes, which require significant transformational efforts to manage due to their high interdependence with other elements of the system. By understanding the high-leverage dynamics surrounding these deep nodes, it was possible to identify a more effective management of cascading impacts without directly addressing the deep nodes themselves, which are more difficult to influence. For example, in the PRB, managing the deep leverage node "Cost of water" was more effective by addressing the link between "GW availability" and "Cost of water," highlighting the transformative potential of this integrated approach.

Finally, uncertainty analysis underscored that leverage points are inherently random. Stochastic simulations showed that high-leverage links, such as between "Average water quality" and "SNA decrease rate" in the PRB, vary in strength and activation over different runs. This confirms that leverage points are probabilistic entities, in line with the literature's call for explicit consideration of random uncertainty in modeling complex systems (Beven, 2016; Montanari, 2011). This insight enhances socio-hydrological perspectives by showing that intervention opportunities in human-water systems are not static, but probabilistic and emergent.

4.2. Addressing Uncertainty in Nexus Systems for Managing Cascading Impacts

Compared to the existing literature, the proposed modeling process represents an advancement in dealing with epistemic and aleatory uncertainty within Nexus systems. These two aspects of uncertainty, which are crucial for understanding cascading impacts and designing effective strategies in WEF Nexus systems, are indeed often overlooked by traditional modeling of complex systems (Beven & Smith, 2015). In this work, a holistic framework for managing uncertainty and its implications on system behavior and decision-making was proposed. To do that, system behavior analysis, stochastic methods, and sensitivity analysis were combined within an SD modeling framework. Specifically, epistemic uncertainty was addressed by refining the understanding of system dynamics through iterative analysis. Structural analysis of CLD using eigenvector centrality identified leader variables of the Nexus system; feedback loops analysis expanded the list of those key variables revealing dynamic interconnections within the balancing and amplification processes. MICMAC analysis defined the role of the key variables, distinguishing between areas of intervention (i.e., leverage points) and those to be monitored. Finally, the integration of SF modeling and LTM expanded the information on leverage points quantifying their evolution over time and under different conditions. Besides that, stakeholder engagement incorporated local knowledge and context-specific factors, enhancing the model's representation of feedback loops, interdependencies, and leverage points as well as accounting for transdisciplinary perspectives in Nexus systems management. These methods provided an in depth understanding of Nexus system dynamics and management.

Aleatory uncertainty, stemming from inherent randomness in Nexus systems, was addressed by incorporating probability distributions into key fluctuating variables. For the PRB, parameters such as "groundwater (GW) recharge rate", "Average crop unit water need", and "Population" were modeled with stochastic variability, reflecting the unpredictable nature of environmental processes and human behaviors. This probabilistic approach revealed the inherent uncertainty of high-leverage loops and links, specifying which of them remain influential across diverse stochastic runs. Besides that, the probabilistic approach contributed to the understanding of the behavior over time of key system outcomes (i.e., the variables to be monitored). In particular, the PRB monitoring variables showed consistent trajectories under deterministic and stochastic conditions, validating deterministic simulations while expanding insights into variability ranges. The relatively narrow uncertainty bands suggest low to moderate sensitivity of the model to the chosen parameter ranges. This implies that, although parameter fluctuations within plausible limits, vary across plausible ranges, the system's overall behavior remains robust and consistent across simulations. Scenario analysis was then used to test measures like improving "irrigation efficiency", "landuse planning regulation/actions", and "farmers' training and awareness". These interventions, targeting the identified leverage points, were shown to improve the monitoring variables under different conditions. The relatively low sensitivity observed across the intervention scenarios reflects a well-documented characteristic of complex dynamic systems, where multiple delayed feedback loops, accumulations, and nonlinear interactions mediate the impact of policy changes over time. As highlighted in SD literature (Forrester, 1961; Sterman, 2000), such systems often exhibit slow and dampened responses. It is important to emphasize that low sensitivity does not imply low relevance or ineffectiveness of the interventions. Rather, it confirms the consistency of the model's behavior with real-world dynamics, where for example, improvements in "Average agricultural sustainability" tend to unfold gradually. These dynamics are cumulative and often require sustained efforts to become visible. Therefore, the model results provide meaningful insights for long-term policy planning, even in the absence of dramatic short-term shifts.

5. Main Limitations and Future Steps

The proposed modeling process addresses the complexity, non-linearity, and uncertainty of Nexus systems by supporting the identification of leverage points and cascading impacts. However, some limitations remain. The structure of both the CLD and SF model may influence leverage point identification and system behavior analysis. In the PRB case, the dominance of deep leverage points may stem from strong interconnections between the variables. Refining system boundaries and including fewer interdependent variables may better capture system dynamics and also reveal shallow leverage points. Furthermore, discrepancies between the structures of the CLD and SF models may reduce the consistency of the approach, highlighting the need for better alignment.

The development of the model, led by analysts with water-focused expertise, may have limited the discovery of unexpected dynamics related to other sectors biasing the results toward water-oriented leverage points. For this reason, a broader disciplinary input in constructing the model is necessary for mitigating this problem (see e.g., Razavi et al., 2025). Furthermore, as Sterman (2000) noted, subjectivity in the selection of variables and probability distributions may introduce biases in the modeling results, particularly for non-physical ("soft") variables, for which data sets are hardly available.

Future work should focus on two aspects. First, systematic methods to validate the influence of leverage points across simulations should be developed, with a focus on that variables for which reliable data are lacking. Second, the modeling process should be applied to different contexts, including those involving extreme climate events (e.g., droughts or floods) coupled with socio-economic and infrastructural challenges. Exploring these additional scenarios may help minimize the risk of unexpected cascading impacts and further refine the approach. This would enhance its effectiveness as a tool for complex systems management toward sustainability and disaster risk reduction.

6. Conclusions

This work dealt with the complexity, non-linearity, and uncertainty of Nexus systems management, thus offering more insights for Nexus doing. Leverage points (areas where small changes may yield significant impacts) are already known as strategies for effectively managing Nexus systems, but they are typically treated as static entities, overlooking their dynamic and uncertain nature.

The proposed modeling process applied SD modeling to capture interactions driven by feedback loops in Nexus systems, combining qualitative and quantitative SD modeling tools (i.e., CLD and SF modeling) with other system-analysis methods (i.e., Centrality Measures, Impact Matrices, and stochastic approaches). This enabled the identification of key system factors, classifying them as leverage points or monitoring variables. The results showed that leverage points, defined in this work not only as nodes but also as links and loops, are dynamic and uncertain. They activate with varying intensity and under specific conditions, depending on the system's state and scenario. In terms of monitoring variables, the modeling process showed that deterministic and stochastic simulations produced similar trajectories, confirming the reliability of deterministic models. However, the stochastic approach offered additional insights by capturing variability ranges. Lastly, leverage points that consistently recurred across simulations proved instrumental in guiding effective interventions during critical system transitions.

The proposed modeling process was applied to one of the case studies from the REXUS and LENSES EU projects, specifically the PRB. Nevertheless, it offers a versatile guide for managing complex Nexus systems and guiding targeted interventions in different conditions, making it applicable to other contexts as well.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

The data and equations within the Stock and Flow (SF) model are provided in Text S5 in Supporting Information S1. The model and data developed in the study are available at Zenodo (Coletta et al., 2025). Vensim® DSS version 10.1.3, used for developing the SF model, is a commercial software. For personal and educational use, a free version (Vensim® PLE) is available. The Loops That Matter (LTM) method was implemented using Stella Architect, which offers a limited-time free trial version.

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