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Representing causal knowledge in environmental policy interventions: Advantages and opportunities for qualitative influence diagram applications

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Abstract

This article develops and explores a methodology for using qualitative influence diagrams in environmental policy and management to support decision-making efforts that minimize risk and increase resiliency. Influence diagrams are representations of the conditional aspects of a problem domain. Their graphical properties are useful for structuring causal knowledge relevant to policy interventions and can be used to enhance inference and inclusivity of multiple viewpoints. Qualitative components of influence diagrams are beneficial tools for identifying and examining the interactions among the critical variables in complex policy development and implementation. Policy interventions on social–environmental systems can be intuitively diagrammed for representing knowledge of critical relationships among economic, environmental, and social attributes. Examples relevant to coastal resiliency issues in the US Gulf Coast region are developed to illustrate model structures for developing qualitative influence diagrams useful for clarifying important policy intervention issues and enhancing transparency in decision making.

Keywords

Influence diagrams; causality; evidence-based policy; coastal resiliency; watershed conservation practices

Introduction

Environmental policy issues are complex, with numerous interacting variables that influence the occurrence of beneficial or costly outcomes. When faced with conflicting perceptions and uncertainties, decision analysis processes are recognized as a valuable means to improve the incorporation, weighing, and evaluation of information and communication of the knowledge base for policy development (Linkov and Moberg 2012). Balancing the data streams and sources of expertise required for large-scale environmental policy planning is a

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challenge that has spurred the application and development of decision analytical processes and methods as an organizing principle for environmental policy (Kiker et al. 2005).

The causal thinking behind the development of policy interventions often needs clarification for communicating and appraising management actions. As stated by McGinnis and Foege (2000), we live in a "cause-and-effect world." It could be assumed that everything in the world is established through causal relationships, and environmental systems can be viewed as stochastic processes of causally interacting factors and unpredictable occurrences. Likewise, the prospects from decisions arise from a causal process initiated by a choice (Sloman 2005). Environmental management relies on an understanding of this causal process and how interventions may or may not work when implemented. Causal models of social–ecological systems are useful for designing policy interventions, but are often not readily available at a project's outset. The uncertainties in identifying system components and causal relations are related to incomplete identification issues (Zio and Aven 2013). A conceptual modeling framework that is adaptive and useful for a wide class of policy problems should help to reduce issues related to incomplete identification and the resulting lack of transparency.

Identifying the causal relationships that show the risks and opportunities in a problem can lead to better clarity in decision making (Tan and Platts 2003; Montibeller and Belton 2006). In particular, qualitative influence diagrams (QIDs) can be useful decision analysis tools for capturing and organizing causal knowledge. The present paper explores how some of the formalisms used in QID construction, including such concepts as random variables, conditional independence, influence pathways, and dynamic Bayesian networks, can assist in developing QIDs for representing structural knowledge of causal influences and interactions among strategic policies and sociological and ecological systems. We suggest that QIDs organize and display causal knowledge of the objectives of stakeholders and policy interventions in a structured and understandable format suitable for qualitative exploration and development of policy interventions. Several classifications for component variables in policy systems and their hypothesized causal links are provided that have broad relevance across many policy development contexts. The linking of variables through QIDs to represent causal structural knowledge is described through demonstrations pertaining to coastal restoration and protection issues. Many coastal regions are currently facing important problems requiring a large base of expertise, including scientific and traditional knowledge, which could benefit from the knowledge representation strengths of QIDs (Francis et al. 2011).

Foundational aspects

Assessing system interventions for evidence-based policy and decision making

The foundation of the QID properties discussed in the present article comes from multiple disciplines, especially from Cain (2001), including ecological risk assessment and Bayesian network applications in environmental assessments. However, evidence-based policy and structured decision making are 2 fields that provide especially useful examples of QIDs and their capabilities for providing insights for decision making.

In evidence-based policy, assertions regarding the effectiveness of planned management interventions might be examined by first capturing important causal structural information on the outcomes and impacts of the policy interventions with conceptual models. This process, briefly discussed here, is exemplified by the Task Force on Community Preventive Services (TFCPS) and described in The Guide to Community Preventive Services (Community Guide; TFCPS 2005). The TFCPS was first initiated in the 1990s, and was built on evidence synthesis practices for individual-based medicine in clinical scenarios. These methods were adapted for examining the effectiveness of interventions to improve public health in communities through interventions implemented within locales such as neighborhoods, healthcare systems, recreational areas, schools, and workplaces.

One key aspect of the Community Guide is the development of foundational conceptual models to inform the analytical aspects relating proposed interventions, the system being intervened on, and the intermediate and health outcomes of concern (TFCPS 2005). Two types of conceptual models are used by TFCPS (2005): logic frameworks and analytic frameworks. In the early phase of the analysis, logic frameworks are developed to capture the knowledge from stakeholders, experts, and existing data to communicate “the nature of the problem” and the relationships in the conceptual model that will be or will not be reviewed (TFCPS 2005). The logic frameworks contain information on the types of intervention and intermediate outcomes, influential factors affecting outcomes, what the interventions are expected to influence, and the connections with the objectives or health outcomes. The logic framework is used to choose and define the interventions that will be focused on for the systematic reviews. Analytic frameworks are then developed to describe the causal pathways from the intervention to the health outcomes of concern in greater detail (see TFCPS 2015 for an example). The development of the analytic frameworks sets the stage for an analysis plan to examine the effectiveness of interventions and is used to frame the results of the review.

Conceptual models also have an important history in decision analysis, especially since the development and adoption of influence diagrams (IDs) beginning in the 1970s. The role of IDs in assessing consequences of decisions and calculating expected utility is well established. More recently, the qualitative portion of IDs has been exploited in deliberative decision analysis processes to capture key information on causal relationships between decisions and objectives during cognitive mapping exercises and workshop discussions. For a decision analysis–focused process, the development process of conceptual models can help support the identification and definition of qualitative components utilized in decision analysis frameworks such as the objectives, performance measures for the objectives, and alternatives. Gregory et al. (2012) list the areas in which IDs can assist in a structured decision-making process:

1. Influence examination
2. Information sources for causal assessments
3. Uncertainties and disagreements
4. Interventional influences on fundamental objectives

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5. Performance measure identification
6. Data sources for performance measures
7. Intervention identification and exploration.

Often IDs will be built through an iterative decision analysis process that updates problem domain schemata and reflects a “common understanding” of the important relationships in the decision at various points in time (Gregory et al. 2012). The learning that occurs throughout a decision analysis process may be on the factual side as well as the values-based side (Gregory 2002), and both of these can be supported by the development of a QID. Qualitative influence diagrams are constructed to assist with deliberative processes to capture key information as conversations are happening and through more structured cognitive mapping exercises (Gregory et al. 2012). The ID building process can start in early phases of decision sketching to initially separate the causal factors from the objectives or endpoints of concern of the problem (Gregory et al. 2012), to more detailed IDs for evaluating decisions, to implementation and adaptive management where the structure (and conditional probabilities) is updated as knowledge of causal relationships improves from experiments and observations (Nyberg et al. 2006).

Qualitative influence diagrams can assist and guide both environmental evidence-based assessments and/or decision problems for structuring key information and uncertainties. The components, variable flow, and pathway analysis tools discussed in this article were synthesized from existing literature to develop a framework that is generally useful across a broad spectrum of environmental evidence-based policy and decision analysis applications.

Variables and interventions

Two important components of modeling decisions are the actions being contemplated and the intermediate and final outcomes (Cain 2001). We represent actions and outcomes as interventions and random variables, respectively. Interventions would contain distinct actions that are being contemplated by management for increasing resiliency or minimizing risks to a social–ecological system. Random variables would encompass a set of possible outcomes on a variable. They may be continuous or discrete, but always represent a set of mutually exclusive outcomes. An example of a continuous random variable might be a water quality variable for dissolved O in milligrams of dissolved O per liter. Discrete outcomes could contain states of true or false, yes or no, good or bad, et cetera. Variables are further broken down into useful types in the next section. Unlike random variables, interventions do not represent uncertain outcomes but contain a set of specific and distinct actions available to a decision maker, and only one of these actions may be selected (Howard and Matheson 2005). The only factors that should usually be viewed as being under complete control of the decision makers in the QID are the interventions. Defining management interventions and the random variables and their scales brings greater understanding and improved communication. However, in early exploratory phases, interventions and variables might lack a clear definition beyond an intuitive one (Howard 1989). Having vague components might be useful in early decision sketching periods, but a more comprehensive understanding of the actions and potential outcomes should ultimately be sought to minimize misunderstanding, to ensure the model is testable and verifiable, and to enhance identification of the components and relationships of the model and the decisions and outcomes being evaluated (Howard 1989). The clarity test (Howard 1988; Clemen and Reilly 2014) is useful to ensure that the variable outcomes and interventions are well enough defined for a representational model of an important decision.

Representing key variables and interventions with a logic framework

There are ways of classifying variables to assist the generation of QIDs in cognitive mapping sessions with analysts and/or stakeholders. Causal impacts of interventions are usefully conceptualized in the logic framework approach described in TFCPS (2005). The logic framework can capture the major interactions in a social–environmental system that an intervention needs to pass through before achieving objectives (TFCPS 2005). The analytical reasoning and developmental approach behind logic frameworks can be applied more broadly to environmental management issues that include ecological, public health, and other social outcomes. The schematics and components used in this section draw upon and adapt the Bayesian network framework of Cain (2001), coastal management in Louisiana, USA (CPRA 2012), and the logic frameworks used in TFCPS (2005) to propose useful variable types that are commonly suitable for most QIDs in policy interventions.

A QID using a modified logic framework was adapted from the modeling framework, figures, and discussions in Louisiana's Comprehensive Master Plan for a Sustainable Coast (Coastal Protection and Restoration Authority [CPRA] 2012) (Figure 1). We view logic frameworks as a useful and general form of a QID that provides a truncated and broader resolution of the environmental management context. The Master Plan is a coastal management document that communicates the evaluation of numerous restoration projects across the state of Louisiana, including baseline alternatives. The actions developed in the Master Plan were designed to optimize future land protection and gains and to minimize the detrimental impacts of land losses (CPRA 2012). The context of CPRA (2012) is naturally focused on capabilities within the state of Louisiana for resolving coastal issues. The models described in CPRA (2012) and appendices provide detailed information on spatial and temporal factors related to the Louisiana coastal system that would further explain the interactions and considerations of the different factors in Figure 1, including how time and spatial scales are integrated. The components and connections in the logic framework of Figure 1 were taken from the organization and discussions in CPRA (2012) and matched to the logic framework components discussed in the rest of this section.

The first class of variables contains "impacts" reflecting the consequences of interest (Margoluis et al. 2013). These variables represent what is important to achieve or avoid from a decision and include both positive and negative outcomes. The impacts are in blue-shaded boxes of Figure 1 showing the decision criteria from the Master Plan in 2 categories (environmental and human impacts). The 2 primary objectives of the Master Plan are reducing flood risk to communities from storms and waves and building land (CPRA 2012). Additional benefits from coastal restoration are used to support and focus the 2 primary objectives, including impacts on ecosystem services, strategic and historic asset protection, and distribution of risks. Because the impacts are the endpoints of the decision, their identification takes primacy (Keeney 1992). A useful way of building and defining impacts

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is through decision analysis tools such as objectives hierarchies (Clemen and Reilly 2014). The second class of variables, “interventions,” defines the actual management actions. Each intervention (e.g., oyster barrier reef construction) will include several actions that vary in type and intensity, including a “no action” intervention for examining the benefits or costs. The third class of variables is “system variables,” which pertain to changes in social and environmental systems from policy choices. They are focused on uncertain possibilities in a system that can ultimately influence the resulting impacts. Identifying and establishing the links between system variables rely on factual understanding that includes social, epidemiological, and ecological knowledge and can come from scientific information, past data, or traditional knowledge. The system variables and their relationships in Figure 1 were taken from the general conceptual modeling structure of CPRA (2012), and arcs represent the flow between the inputs and outputs for each modeling group. The next variable class is “controlling variables,” which represents causes or forcing factors to the system that are outside of the influence of any possible interventions (Cain 2001). Controlling variables have a potential necessary and/or sufficient influence on the outcome of a decision but are not influenced by the choices available in a policy context. The system variables would be endogenous (attached to a system), while the controlling variables would be exogenous (outside of the delineated system) (Koopmans 2014). In Figure 1, the controlling variables include watershed influences such as discharge and nutrient delivery, along with oceanic and atmospheric influences that are not under control of the decisions being contemplated (CPRA 2012). A controlling variable can be identified by its being located outside of the causal pathway between the interventions and impacts.

When developing a system model for complex problems, the complexity can be overwhelming, difficult to display, and difficult to reason with. Qualitative influence diagrams like the modified logic framework of Figure 1 can be developed in initial screening discussions of the system components, the outcomes of interest, or the intervention types. There might be useful information to track or keep available on potential causal interactions that would be difficult to display in full detail. Detailed QIDs can be developed at the back or front end of the problem formulation process. The clarity of the logic framework approach in Figure 1 for summarizing the key components of an intervention can be supported by QIDs with greater detail on the causal interactions among interventions, system variables, and ultimate impacts of concern if required.

Causal pathways

The relationships among the variables related to interventions, system components, and outcomes can be further defined and causally mapped within a QID. The logic framework approach of the TFCPS is used to capture broad contextual issues, but an analytic framework is also created by the TFCPS to detail the pathways from the interventions being tested to intermediate and health outcomes of importance (TFCPS 2005). Subsequently, proposed interventions are evaluated with the evidence base for implementation recommendations, bias in the available evidence, and overall information availability (Anderson et al. 2005). The following sections explore how QID structures can be used to support this process of diagramming more detailed aspects of the intervention, the system variables intervened upon, and the outcomes of concern.

The intervention and variable types are isolated in the next examples and expressed as nodes (circles) in diagrams. Arrows or arcs are utilized to signify a direction from a cause to an effect in a respective parent-and-child relationship between nodes. Absence of a direct arc between a parent-and-child variable implies no causal relation or an indirect one through additional variables in the system. Directionality is necessary for causal attribution. One practical reason is that a cause precedes an effect in most realistic considerations (Korb et al. 2009). However, inferences can be made in multiple directions, even acausal ones that go against the arcs. This mimics real-world observations in which knowing the status of something will change the likelihood that something else might be observed through a correlative relationship that might or not be causal. Our focus here is not on knowledge flow but on interventional influences throughout a system. All QIDs from this point forward were built in Bayesialab 5.4.3 (Bayesia S.A.S. 2015). Also, for simplicity, intervention nodes will be represented with circles, like chance nodes, and not the square shapes often used (e.g., Dawid 2002; Howard and Matheson 2005).

Causal connections

Analytical judgment is necessary to specify the amount of detail regarding variables and relationships that are included in a QID, but it is important to indicate the critical uncertainties through the presence of nodes in a QID and to include important considerations for the end users of the QID. Similar to the classes of variables, the relationships between the variables can signify useful information. The basic types of causal relationships or causal fragments used for building QIDs are displayed in Figure 2. Several different types of connections are highlighted. The first is a serial connection between nodes in Figure 2a that expresses a causally ordered relationship. As described in GoCoast2020 (2013), an expert and citizen report developed by the state of Mississippi for the Gulf of Mexico restoration, a seafood marketing promotion intervention can be designed to influence industry awareness, including chefs and restaurants, of the quality and benefits of the seafood which in turn is passed on to consumers. One key consideration is the notion of causal independence. In Figure 2a, we assume that the marketing program does not causally influence the extent of consumer awareness, except through the seafood industry. Thus, “Seafood marketing program” has a separated relationship with “Consumer awareness” through “Industry awareness.” If there were other aspects of the marketing program, such as advertisements, that influenced consumer awareness, then we could represent this in the simplest manner, through Figure 2b. Here, we are communicating that the marketing program influences the consumer awareness directly and indirectly through the industry. Both Figure 2a and Figure 2b could be further diagrammed to include more detail such as additional mediating factors that influence the impacts of the marketing campaign on both consumers and industry and better detail about the interrelationships between the consumers and industry.

A common cause (or diverging connection) is indicated by a node with 2 or more arcs originating (“Fishing gear investment” in Figure 2c). As discussed in Ocean Conservancy (2011), the quality of the fishing gear can influence the amount of bycatch as well as the fuel usage by fishing boats. The QID is also stating that the bycatch has no causal influence on fuel efficiency and vice versa or that this relationship has no causal relevance. If this were not the case, an arc would connect the 2 effect variables. A common effect node (or converging connection) is indicated in Figure 2d, which provides an example of a collider variable or a variable that is an effect of 2 or more causes (“Income”). For current purposes, the collider indicates that income might be determined by both the adoption of certifications for sustainability by the industry and the demand for sustainable seafood.

The basic relationships in Figure 2 are the building blocks for QIDs and for communicating what they imply about the causality and inferential possibilities between system variables. Along with defining the variables and interventions, greater knowledge of potential causal influences can help the developers and users of the model think through the causal implications of the decision and identify new variables, interventions, or potential outcomes. Questions can be designed in interviews to more fully explore the implications of the QID being designed and correct for any misinterpretations based on notions of blocking causal influences between variables. These notions come from assumptions such as d-separation that are outside of the scope of the present article but further discussed and explained in Pearl et al. (2016) and are worth understanding for a rich depiction of causal and acausal inferences with qualitative and quantitative IDs.

Identifying the pathways from interventions to outcomes

Figure 3 provides an integrated model with all of the components of Figure 2 and several additional nodes that might provide valuable information for causal inferences. The arcs that are boldface and blue indicate causal pathways from “Fishing gear investment” to “Income.” A causal path follows the direction of the arcs between a cause and effect and can be intercepted along the pathway by other variables (Greenland et al. 1999). For example, investing in fishing gear might increase fish catch and fuel efficiency, which might provide additional income. The types of fishing gear used can also influence the adoption of certification, which will potentially influence demand for seafood from the region and income to the industry. Bycatch reduction will potentially be influenced by fishing gear investments, which might enhance demand and income. The network compactly displays and helps communicate useful hypotheses regarding causal structural information from the simple building blocks discussed in the previous sections.

Insights from causal pathways with complex QIDs

Causal pathways can also be used with complex QIDs to better anticipate the intermediate and final results from policy interventions. Models that couple environmental and social systems, such as the influence of farming practices on nutrient loadings, can provide greater insights to predictions (Jellinek et al. 2014). This will be demonstrated with a QID for the upper Mississippi River watershed (MRW) that joins education and research systems with multistakeholder processes, uptake of sustainable practices, and outcomes on the physical integrity of the environment. The substantial reductions in nutrient runoff from the MRW needed to lower the size and occurrences of hypoxic dead zones off the Gulf Coast require capacity-building programs that support the needs of local communities. The MRW covers almost 40% of the continental United States and extends into Canada. Farming is an important land use, and the upper MRW provides the highest estimated nitrate yields out of 7 delineated subbasins in the MRW (Turner et al. 2007). The MRW region of interest is a considerable distance from the receiving body (i.e., the Gulf Coast) discussed in the CPRA example. The interventions can lead to changes that influence one of the controlling variables in Figure 1 (“Mississippi River nutrient concentrations”), which is an impact for the current interventions.

From the Peterson et al. (2011, Recommendation 4, p 53–56) discussion of agricultural changes in the upper MRW that might minimize excess nutrient export to the Gulf of Mexico, a QID describing the influence of the establishment of a network of demonstration watersheds on nutrient concentrations in the Mississippi River (MR) was developed (Supplemental Data Figure S1). The Peterson et al. (2011) report discusses a spectrum of intermediate and ultimately desirable outcomes from 2 interventions: 1) developing demonstration watersheds that pursue multifunctional agriculture and 2) changing incentives in the US Farm Bill (H.R. 2642; Pub.L. 113–79; U.S. Congress 2014) to more adequately reflect conservation and commodity goals. A well-designed demonstration watershed program is expected to test, develop, and demonstrate the regional, community, and on-farm benefits of multifunctional agriculture systems. The Farm Bill would ideally allow conservation and commodities incentives to work in tandem with one another and with the demonstration watershed program to allow for greater regional control in farming priorities and establishing sustainable agricultural practices. The focus of the QID is on creating demonstration watershed research and development programs for new agricultural production systems with a single objective to minimize nutrient enrichment in the MR. Key aspects of the discussion of the Farm Bill are represented as controlling variables but not interventions.

The causal pathway from “Production system testing program” to “Nutrient concentrations in river” is highlighted by the arcs in blue (Figure S1). Identifying the causal pathways includes examining which variables are in the pathway or not in the pathway. Determinations of directionality can sometimes be context specific and based on the questions of interest, resolution, and timing of future decisions and system events. From the assumptions in this hypothetical model, the key variables directly influenced by the “New production system evaluation development” possibilities are the “Nutrient runoff reductions,” “Agricultural performance,” “Economic benefits,” and “Timing of benefits” in the demonstration watershed. These in turn have a potential impact on “Working landscape/ multi-functional agricultural establishment,” “Conservation uptake,” “Crop diversification,” “Fertilizer use,” and “Nutrient export” from the broader agricultural region. The latter node influences the target of “Nutrient concentrations in river” (the MR). The network assumes that there are important influences on the success of the demonstration watershed and the relevance of its lessons to the greater agricultural system. The QID communicates these important causal assumptions; the “New production system evaluation/development” process is not a causal factor in the establishment of “[Ecosystem service] ES valuation” and “ES payment mechanisms,” nor in “Integrated management establishment.” However, “Integrated management establishment” will influence the success of the production system evaluation at several key junctures. “Integrated management establishment,” which includes multistakeholder processes, is a causal factor for “New production system evaluation/ development” as well as the potential success of the outcomes from evaluating production systems in the demonstration watershed. Likewise, “Locally appropriate crop development,” “Regional growing conditions,” and “Commodity support” factors from the Farm Bill have an influence on causal pathway variables in the agricultural system. These assumptions are captured in the model and can be utilized to examine the relationships and evaluate whether the important causal relationships and variables are included. Additional cobenefits and costs, including the economic impacts of working landscapes, can also be added in a causal fashion.

During the decision implementation phase, the outcomes on the variables in the causal pathway are ones that are important to monitor or track to ensure that assumptions are being met and that the decisions are on course for achieving their ultimate objectives. In this way, examining the causal pathways is analogous to assessing results chains in which targets are recorded for intermediate variables in the causal pathway leading to impacts (Margoluis et al. 2013). The impact of concern is nutrient concentrations in the MR, but intermediaries such as uptake of conservation practices and lowering fertilizer use through localized crop development must occur prior to a significant change in water quality from the intervention. This application of QIDs can be useful for supporting an adaptive management process. For variables that are difficult to observe due to analytical constraints, intermediate pathway variables are useful for identifying proxies for use with the longer-term performance measures (Gregory et al. 2012). The uptake of conservation practices and export of nutrients from farmlands would be useful short- and moderate-term measures identified from the causal pathway analysis for evaluating demonstration watershed options. The intermediate variables can also be used to track how the nodes outside of the causal pathway (the ones with the thin black arcs) can influence the progress of the intervention and, if at least partially controllable, can further assist in developing beneficial options. An assumption is that Farm Bill incentives are outside of the control of the decision makers for this hypothetical context, but designing indirect or supporting interventions might be possible to free regions from constraints on crop diversification and align commodities with conservation practices. These ideas can help to target the uncertain variables that are important to predict, monitor, and design interventions for assisting the progress of the outcomes on the causal pathway variables in reaching beneficial outcomes. The QID does not provide a quantitative estimate of the impacts of the demonstration watershed on the management objective pertaining to nutrient concentrations in the river. A quantitative Bayesian network or influence diagram approach would be required for this, and the QID would be a useful and necessary precursor to the development of such a model.

Dynamic qualitative influence diagrams

Previous QIDs have considered space and time to be cohesive or implicit within the relationships of the diagrams. We now illustrate how QIDs can better represent space and time while maintaining causal directionality. Our main concern in the following examples is representing resource integrity changes through time and the interventions that can lead to these changes, along with key effects.

Temporal issues with qualitative influence diagrams

Figure 4 presents an example of a dynamic influence diagram (Korb and Nicholson 2011). This QID demonstrates how time can be better considered in the QID process by displaying

3 time steps of interest for seagrass integrity and consumption of the seagrass plants by manatees. Time step 1 (T1) represents the baseline for seagrass integrity and the biomass consumed by manatees as a result of the condition of seagrass. The T1 variables are the controlling variables that will influence subsequent successes and failures of the interventions. The second time period (T2) is affected by the seagrass integrity in the first time period as well as the manatee removal of seagrass (which is viewed as a desirable endpoint, but one that could also have implications for the seagrass in further time periods). The second time step also introduces an intervention of wastewater treatment plant (WWTP) improvements from adding or improving the treatment stages. Time step 3 (T3) is the ultimate time period of interest and integrates the effects from all of the previous time periods. These time steps can be used to characterize “feedback” loops in a nuanced manner that allows considering more relationships as the variables change due to interventions or other variables over time. They can also be used to draw out the time steps of interest for interventions and causal relationships.

Representing space and time

Spatial issues can also be further detailed in a QID to represent outcomes in different regions from 1 or more interventions. Figure 5 illustrates an example for seagrass restoration in 3 separate coastal regions. Two interventions are displayed. The first is nonpoint runoff controls in the terrestrial zones, and the second is transplant efforts in one of the coastal regions. The nonpoint runoff controls will directly affect the water quality in two of the coastal regions. The third coastal region might be further downstream and its water quality would only be influenced by the nonpoint runoff controls from the changes in the adjacent region (R2). The first region is isolated from the second and third regions as far as water quality changes and connectivity for propagule dispersal are concerned.

The time steps in Figure 5 can also be included and combined with Figure 4 to more fully consider the causal relationships across space and time and processes such as propagule dispersal between 2 regions. This is illustrated in Figure 6, which combines the causal relationships in Figures 4 and 5. Although more complex, the time and space integration allows greater specification of the spatial and temporal issues in the intervention problem and provides a much richer picture of the causal interactions. For example, R3 is shown to influence seagrass integrity in R2 through propagule dispersal, as well as R2 influencing R3 by the same process through including space and time. Constructing the intervention in this manner can help to maintain useful detail. The issues can also be succinctly summarized in a logic framework such as in Figure 1, with the more complex ideas still represented in a commensurately detailed fashion.

The causal pathways between WWTP improvements and seagrass integrity at R3 and T3 are detailed with boldface blue arcs. The pathway highlights how water quality changes as well as biological condition changes in R2 from this intervention would influence seagrass at R3, which is anticipated to begin to occur between the second and third time steps. The connections between time periods can be viewed as interval censored in event analysis terms, given that they delineate only that a potential change might occur by the start of a new time period. Thus, time periods should be developed to be useful to the intervention context, not too detailed and not too coarse, but reflective of important observation and outcome periods for examining the interventions' effectiveness. Adding probabilities into this diagram would further weight these processes and allow for greater consideration of uncertainties in the causal influences between time periods and regions. However, networks with large conditional probability tables (CPTs), which tabulate the probabilities of a node's states given the occurrence of any combination of its parent nodes' states, can be infeasible for computing inferences. Cain (2001) discusses modeling tips for keeping networks tractable in the quantitative stage, and Kjærulff and Madsen (2013) give advanced tips for reducing the size of CPTs. The complexity of the QID can also be reduced as uncertainties are resolved through learning, thereby permitting the removal of uncertain variables from the diagram (Wilson and McDaniels 2007).

Additional qualitative influence diagram building guidance

There are numerous ways a QID might be constructed, but several useful methods or case studies will be referenced here. Arentze et al. (2008) developed and tested an interview protocol for individuals that includes eliciting the variables in a decision problem, determining the order that decisions will be made, and building a causal network. For the present work, the questions in Arentze et al. (2008) can be adapted for identifying system variables and interventions with experts. For scenario development with stakeholder workshops, Tiller et al. (2013) provide a case study examining the concerns about future aquaculture developments with fishers in California, USA. Their application focused on developing future scenarios through identifying variables and then their relationships in workshop discussions and activities using white boards and sticky notes. This method was also exemplified for stakeholders and socioeconomic aquaculture issues in Chile in Salgado et al. (2015) with multiple stakeholder workshops that facilitated the identification of shared concerns. Nadkarni and Shenoy (2004) provide a process for developing and translating causal maps into Bayesian networks. Their method provides guidance on interviewing, coding, and identifying statements in everyday language that can be translated into causal relationships. Cain (2001), whose general network structure was adapted in the present article, provides building guidance for Bayesian networks, including ideas for generating variables, states, and connections, but also provides tips on simplifying initial conceptual models. Advice for developing a useful network from collaborating with stakeholders and conducting workshop discussions is also provided by Cain (2001). As mentioned previously, Gregory et al. (2012) describe multiple examples of QID development in clarifying workshop discussions and identifying objectives and performance measures, as well as for quantitative model development. Belardo and Harrald (1992) describe techniques for hindcasting (in which a terminal event is used to construct previous events in time). The other references are more general in their potential applications, but hindcasting may be particularly useful for contexts in which unlikely but significant consequences are a concern because it helps experts envision the situation that could lead to the occurrence of a desired or undesired state (hindsight is 20/20). Hindcasting has been applied to low-probability scenarios with significant potential impacts, including oil spills, Red Cross disaster planning, and bank regulation (Belardo and Harrald 1992). Hindcasting exercises for oil spill planning and how the knowledge was developed for an ID is described in Harrald and Mazzuchi (1993).

Discussion

The development of useful construction methods for representing causal knowledge can assist in preparing and using this information for policy development, communication, and implementation. The present article demonstrates important features of QIDs that can enhance transparency for policy interventions targeted at minimizing risk and increasing environmental resiliency. The flexibility of QIDs extends to capabilities for usage in conjunction with various other organizing approaches such as result chains for conservation program assessment (Margoluis et al. 2013); scenario construction with stakeholders (Tiller et al. 2013); conceptual model building for ecological risk assessment (Ayre et al. 2014); hindcasting complex, low-probability, high-stakes events such as oil spill disasters (Belardo and Harrald 1992); or synthesizing evidence on risk hypotheses (Newman et al. 2007). The components and connections presented here could also be transferable to a more generalized cognitive mapping approach or ones that rely on other causal graphing frameworks, including causal loop diagrams or systems dynamic modeling. Causal loop diagrams might be useful to summarize problems with many feedbacks over time, as would systems dynamic modeling. The latter can be especially useful for capturing stocks and flows of materials, chemicals, and energy. Bayesian network model fragments outside of cause–consequence relationships will further augment the cognitive mapping and knowledge representation process for policy development (Neil et al. 2000). Representing measurement uncertainties and examining acausal pathways when making inferences are all key benefits of QIDs that were not discussed here, but that add richness to development and interpretation of QIDs.

Developing the causal interactions of a problem with a QID can help augment the search for impacts and interventions. New variables can be identified in the QID process by considering causal scenarios that might occur from intervening on the system or directly on an impact variable. The interventions and system variables can be used to assist in recognizing additional impacts that would be important to track and evaluate. Worst- and best-case scenarios could be given special attention in this process (Keeney 1992). System variables can also be used to develop interventions as in Anderson et al. (2003, Table 1), where intermediate outcomes are further detailed as to their characteristics and the interventions that could potentially lead to improvements. The interventions can be further defined and/or grouped together for comparisons using strategy generation tables to define the elements of a decision strategy (e.g., spatial locations for implementation) and to group multiple actions into cohesive policy portfolios (Howard 1988).

Piecing together the causal associations between variables can help establish an understanding of complex relationships. The “connections and components” of a problem are important aspects of knowledge representation (Davis et al. 1993), and their identification can provide a better understanding of the implications of policy interventions. System approaches to decisions focus on the causal patterns and connections, whereas reductionist approaches tend to be reactive and focus on symptoms (Banson et al. 2016). In multiparty processes for decision making, building a QID can help “demystify” the knowledge and hypotheses regarding causal interactions and can place greater focus on significant factors in a decision problem (Gregory et al. 2012). A QID provides explanations about a problem domain in its structure of dependencies and independencies. Explanatory depth can assist with policy development and support of stakeholders. For example, decision support systems in the medical field had barriers to adoption due to ambiguity regarding the advice the system was providing despite predictive accuracy (Yuan et al. 2011). The QID can also enhance the understanding of the quantitative knowledge of a problem’s features. The qualitative (nodes and states) and quantitative (conditional probabilities and utility scales) components of IDs describe the conceptualization of the decision issue (Carriger and Barron 2011). In scenario development, the qualitative framework is used to support the communication of the quantitative aspects of an intervention (van Notten 2006).

Participatory model development can foster collaborative learning and transparency in decision making (Nyberg et al. 2006), in turn, increasing ownership (Stewart et al. 2014) of a decision. Public engagement with QIDs can enhance understanding of the concerns regarding policy impacts and open dialogue toward mutual understanding regarding how planned interventions can serve the public good. The graphical structure enhances facilitation between managers and stakeholders by making the structural viewpoints apparent. The ability to think causally is something that is readily available to many stakeholders, experts, analysts, and decision makers.

The decision context may or may not need quantitative modeling (Addison et al. 2013), and IDs can be adapted for either situation. Sometimes the QID will move a decision forward but can still serve as a precursor for future quantitative applications (Marcot et al. 2012). The interactions between qualitative and quantitative model development can assist in determining the information needs and the degree of precision required. Even in areas lacking data and rigorous observations, the construction process can incorporate the beliefs of stakeholders about their well-being and represent what information is needed and where structural disagreements lie. The problem features are much more likely to withstand changes in time than are the quantitative values that are often “ephemeral” in comparison (Smith 1994).

Conceptual models can be too easily compared to reality. Uncertainties can be daunting in many environmental management activities, and conceptual models can often mask the uncertainties in decision pathways. Upstream variables can often have highly uncertain links to downstream objectives. These quantitative features that elucidate the uncertainties in the problem domain are missing in QIDs (Greenland et al. 1999). However, qualitative network development provides a crucial step in the construction of Bayesian networks and sets the stage for parameterization (Lucas 2005). For risk assessment, the preliminary sketching of a problem with a QID can emphasize the important uncertainties that must be understood (Morgan 2005). The addition of probabilities and stochastic properties to the model does not conceal the QID’s representation of causal knowledge about the problem(Cox Jr 2012). Translating QIDs to quantitative frameworks will open the analysis to many important interpretations through sensitivity and uncertainty analysis and can ultimately move the embedded notions and hypotheses into judgments (Edwards 1991–1992).

Dynamic and fluid decision-making processes that are sensitive to evidence, issues, and needs are increasingly being applied. Scenario planning (Tiller et al. 2013; Russell-Smith et al. 2015) can be adapted to help construct the vision stakeholders hold for a desirable future and combine it with factual knowledge and uncertainties to guide resource management in an iterative QID development process. Influence diagrams can easily be adapted to dynamic situations and updated as new data and knowledge become available. In an iterative model development process, QIDs can assist in better understanding the problem domain, including representing the key issues and currently accepted and debated solutions and the use of domain knowledge for identifying data needs (Cios et al. 2007). Identifying the important uncertainties in a problem, including ones that come outside of environmental processes, and targeting uncertainties that might be addressed are a natural part of the decision-making process (Reckhow 1994; Ascough II et al. 2008). Putting causal models and understanding at the forefront of the analysis and making them explicit can bring about better understanding and testable hypotheses for data gathering. Doing this might reduce errors from intuition and enhance communication and incorporation of knowledge.

Qualitative ID construction can be a natural process for capturing expert knowledge on structural aspects of policy intervention problems. Directed acyclic graph theory provides a coherent and logical approach for focusing on the components of qualitative models that would have relevance to policy design and analysis, especially the causal implications from interventions (Pearl et al. 2016). Environmental management decisions often impact numerous dimensions of social, economic, and ecological systems, making the connective properties of QIDs useful for integrating the different forms of expertise needed for assessing policy. Adopting QIDs in participatory research and management will help avoid black box interpretations of technical issues and will provide a platform that is conducive to integration of diverse ideas and viewpoints.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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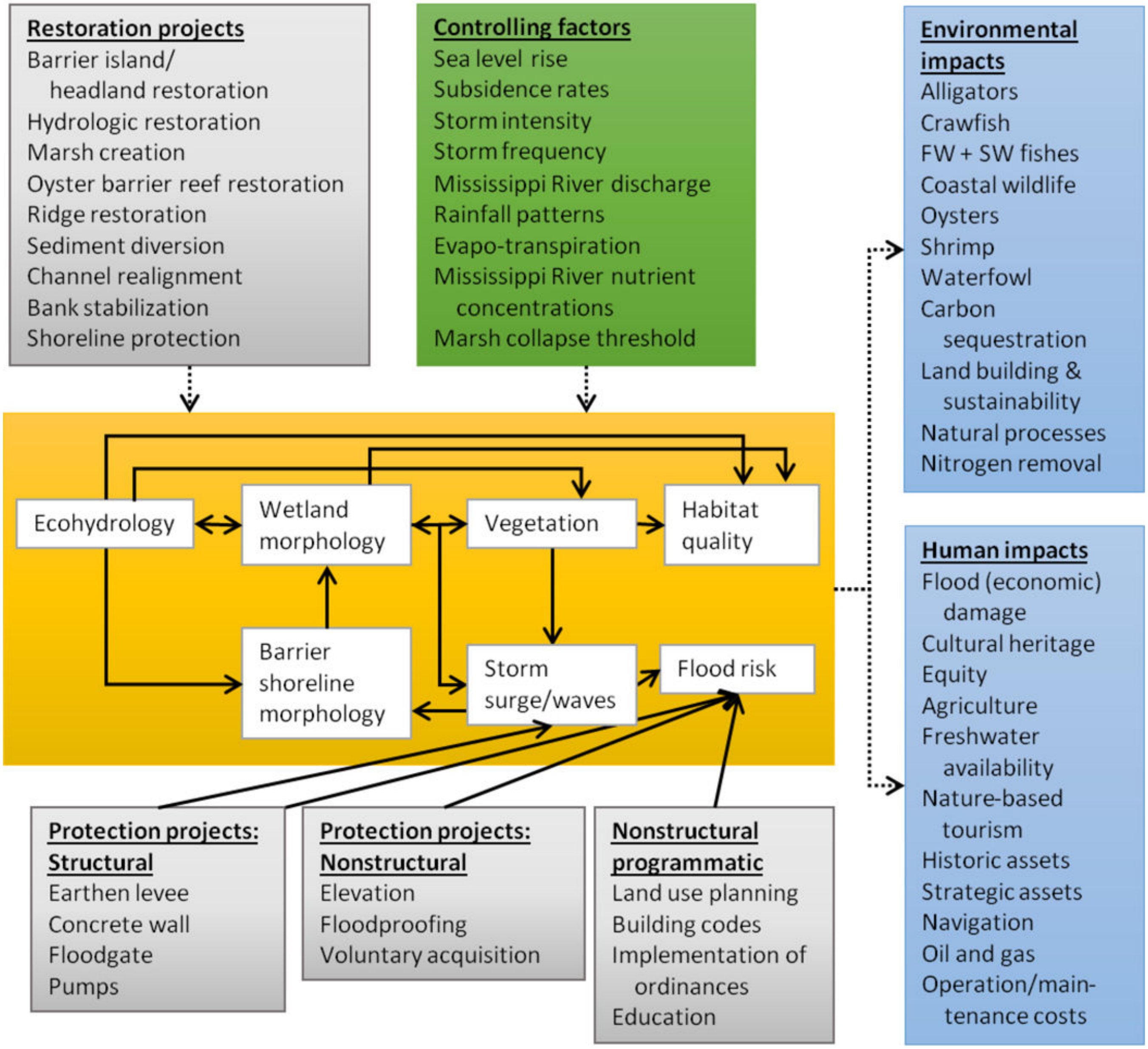

Figure 1.

Qualitative influence diagram demonstrating a logic framework for the causal structure of restoration considerations in Louisiana, USA, coastal restoration (adapted from CPRA 2012). The text in the grey rectangles titled "Restoration projects," "Protection projects," and "Nonstructural programmatic" are the interventions; the text in the green rectangle titled "Controlling factors" shows the controlling variables; the text in the yellow rectangle in the center without a title shows the system variables; and the text in the blue rectangles titled "Environmental impacts" and "Human impacts" shows the impact variables. Dashed arrows indicate multiple causal relationships between inputs and outputs. Solid arrows indicate a specific causal relationship between the interventions and system variables. FW = freshwater; SW = saltwater.

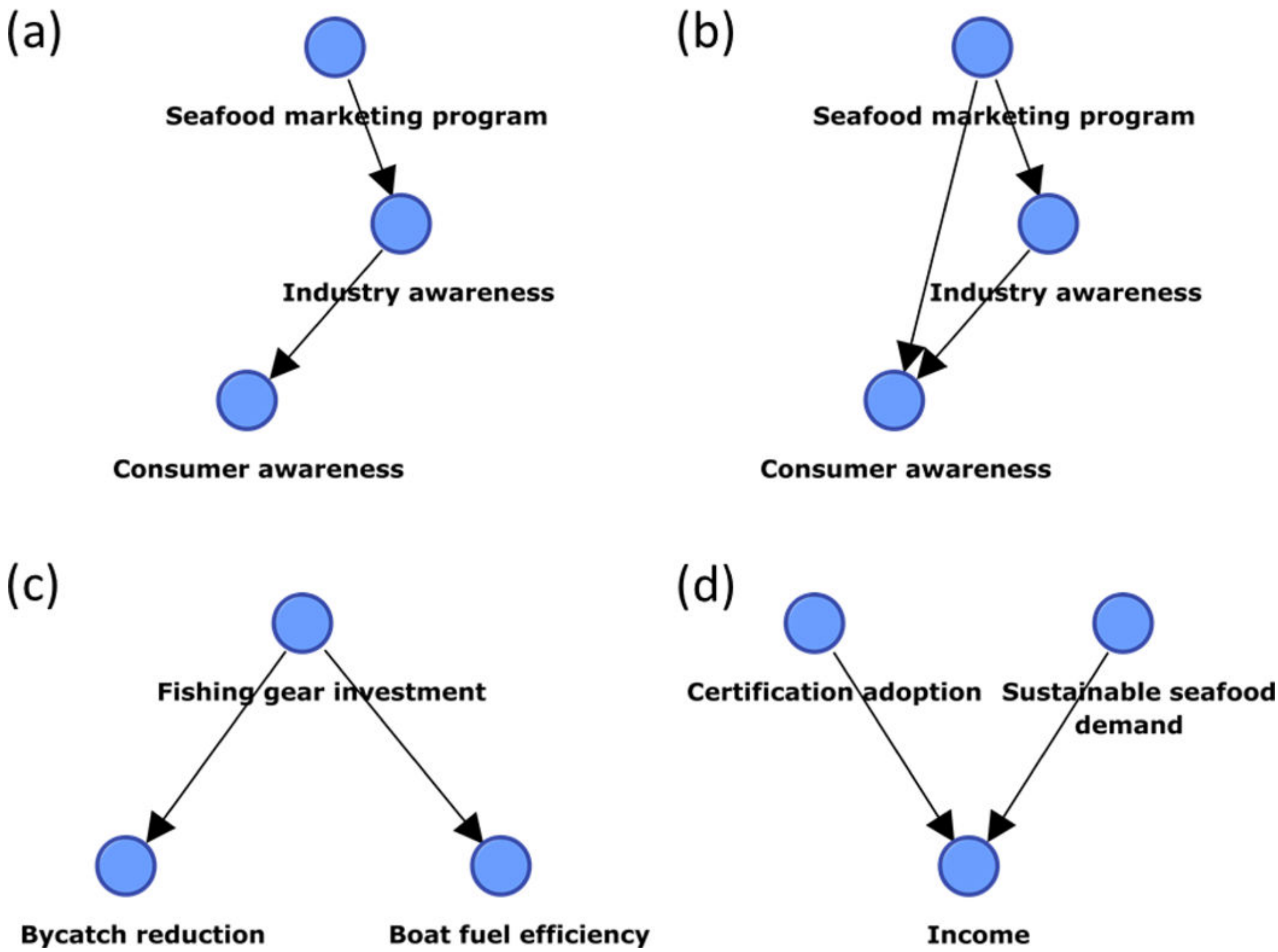

Figure 2.

Examples of causal connections between variables in qualitative influence diagrams: serial causal connection (a); serial causal connection and a shared common effect (b); common cause (diverging) connection (c); common effect (converging) connection (d).

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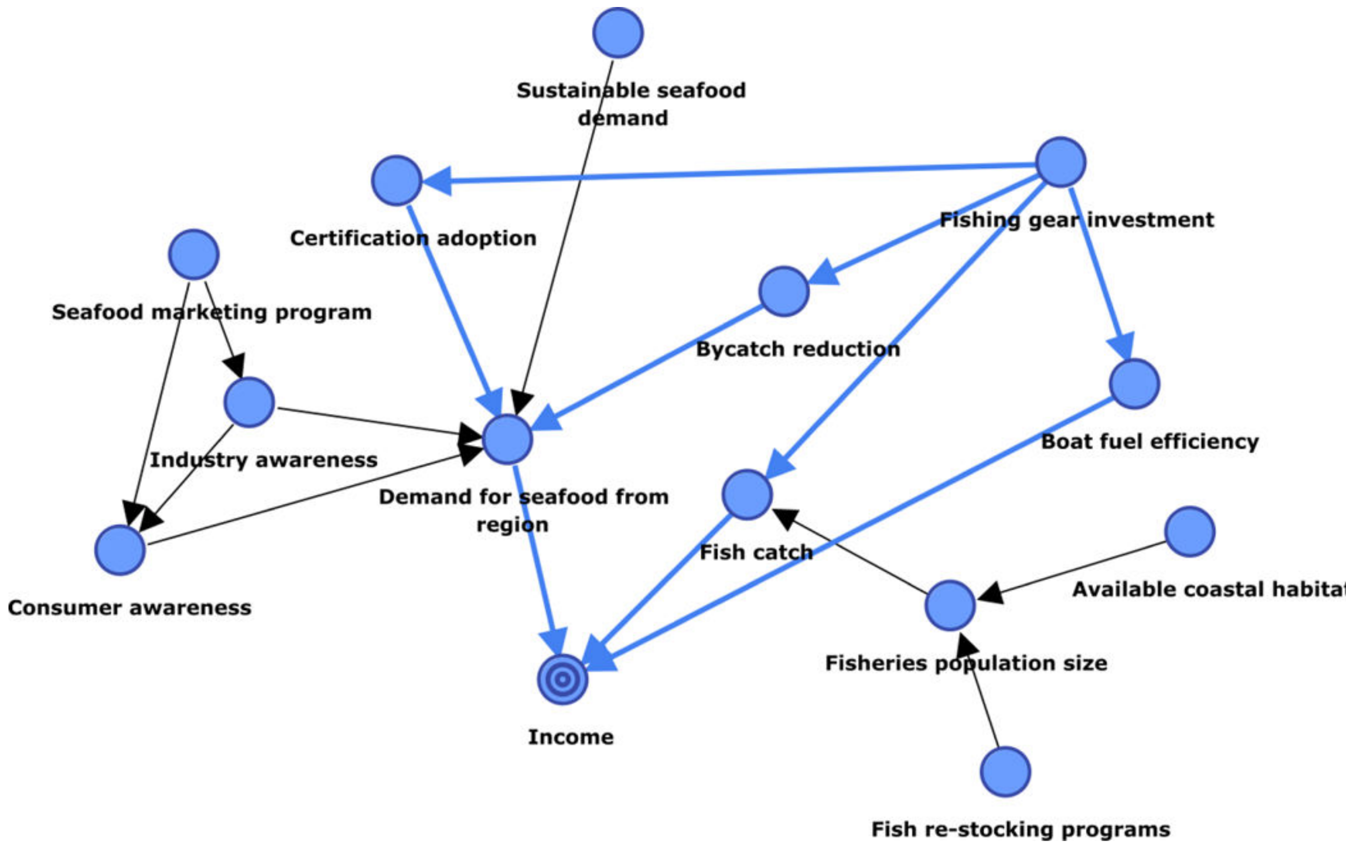

Figure 3.

Qualitative influence diagram examining causal influences on income from developing a seafood marketing program and making fishing gear investments. Causal pathways between "Fishing gear investment" and "Income" are highlighted in boldface blue.

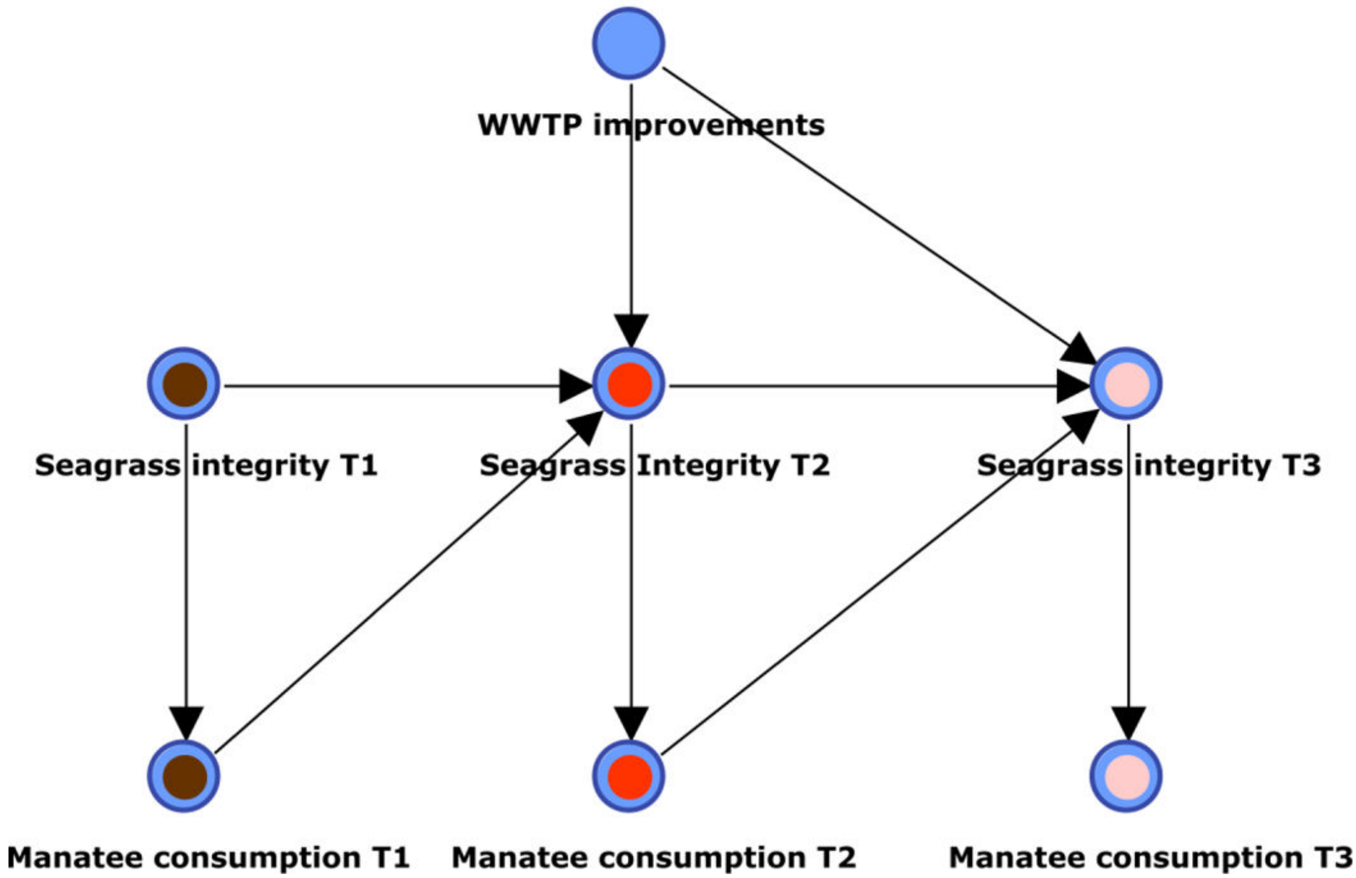

Figure 4.
Dynamic influence diagram examining the causal relationships between seagrass integrity and manatee consumption of seagrass during 3 time periods. Each Ti (i.e., T1, T2, T3) indicates the time step of interest. WWTP = wastewater treatment plant.

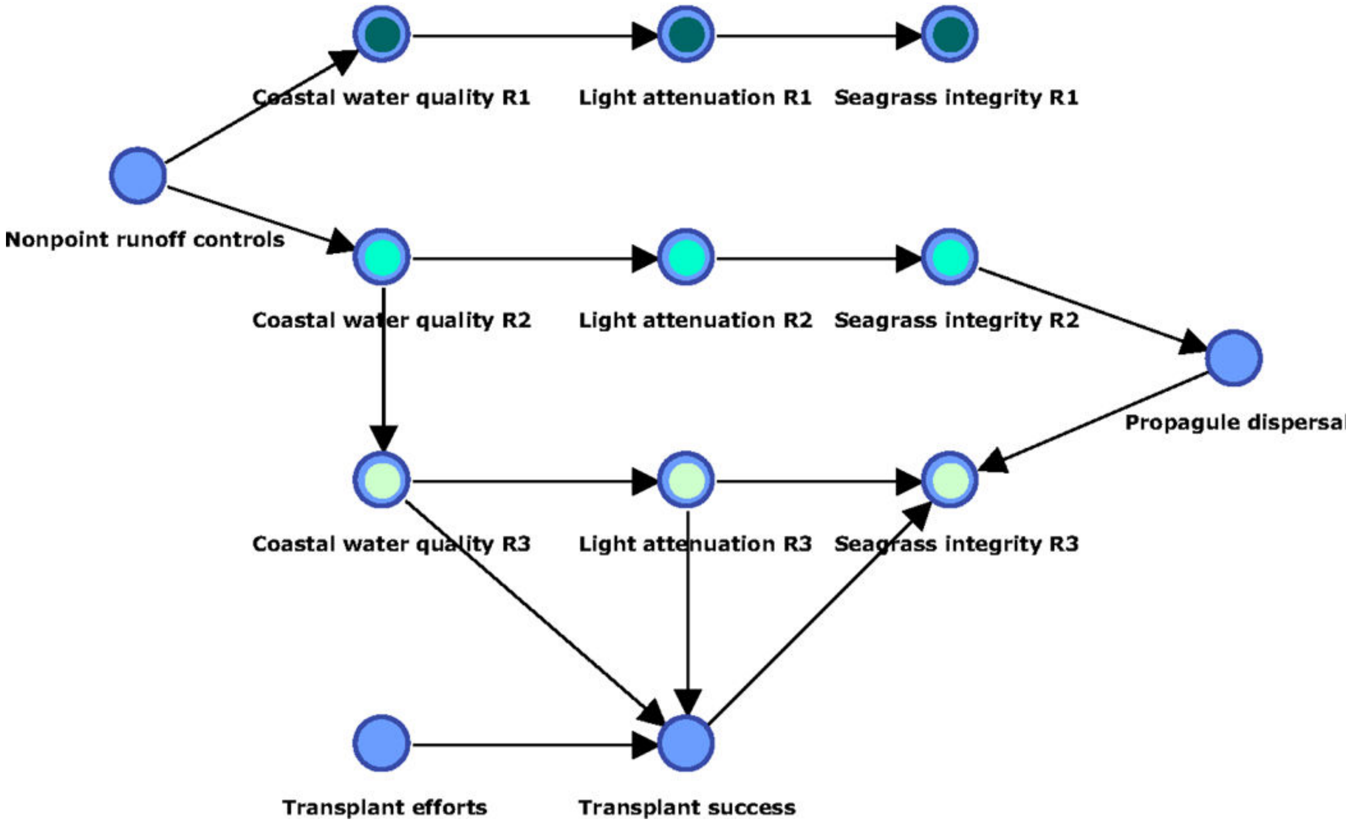

Figure 5.
Spatial qualitative influence diagram examining seagrass integrity at different regions of a coastal system. R = region.

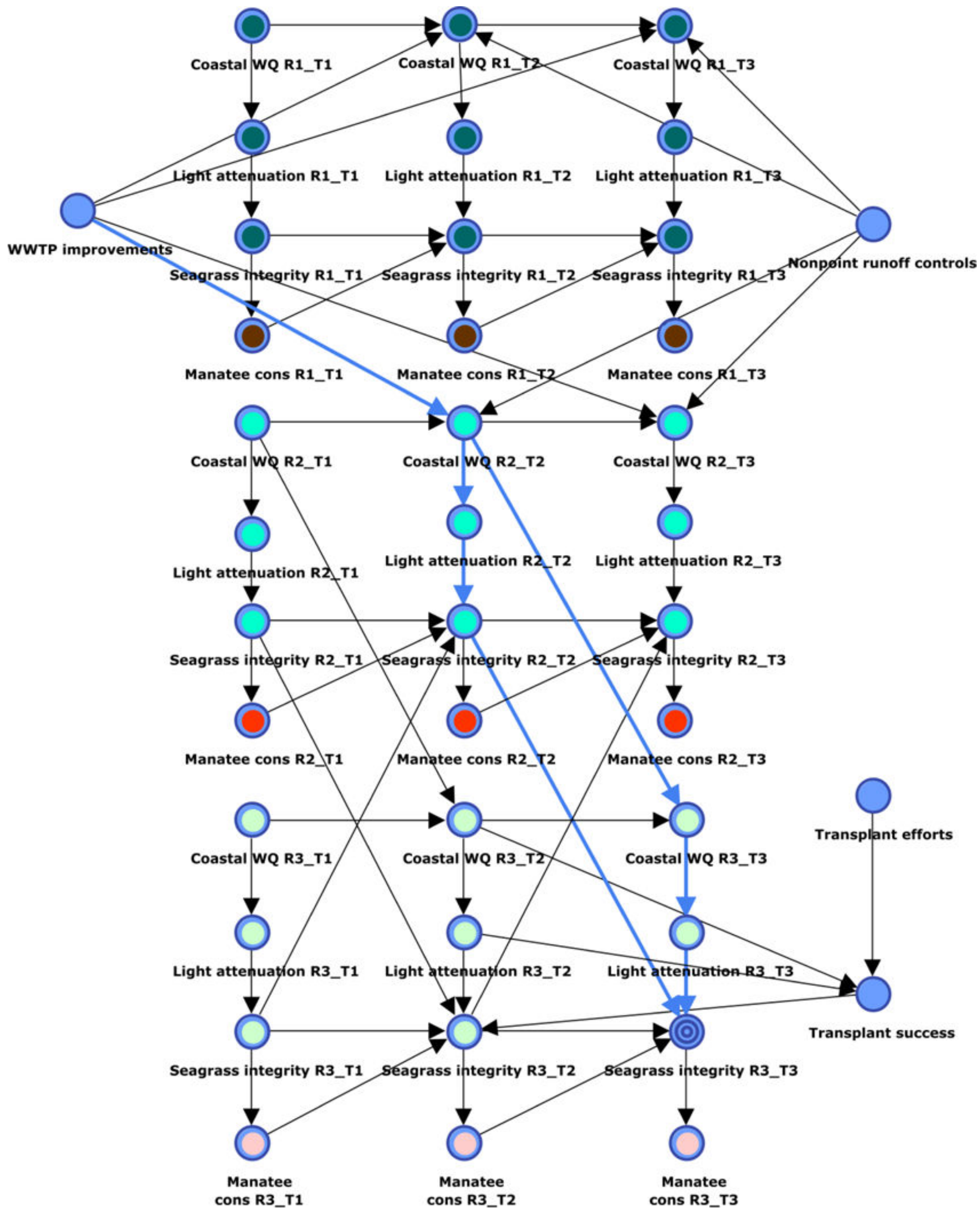

Figure 6.

Qualitative influence diagram representing space and time issues in coastal seagrass restoration interventions. Blue arcs indicate causal pathways from WWTP improvements to seagrass integrity at Region 3 in time step 3. Cons = consumption of seagrass; R = region; T = time period; WQ = water quality; WWTP = wastewater treatment plant.