

EXAMINING THE MENTAL MODELS OF PRESERVICE TEACHERS ON A
CLIMATE CHANGE BASED CASE SCENARIO WITH THE SYSTEMS
THINKING APPROACH

by

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ABSTRACT

EXAMINING THE MENTAL MODELS OF PRESERVICE TEACHERS ON A CLIMATE CHANGE BASED CASE SCENARIO WITH THE SYSTEMS THINKING APPROACH

Climate change is one of the complex problems due to its dynamic nature and interactions. However, people tend to have simple and linear mental models. Thus, it is necessary to approach climate as a system and go beyond simple mental models to address climate change. Given the role of education, it becomes essential for teachers and pre-service teachers to be competent in systems thinking. This study examines pre-service teachers' mental models of a case scenario based on climate change using a systems thinking approach. Data were collected from pre-service teachers enrolled in a climate change education course at a state university through Lake Urmia Vignette developed by Davis *et al.* (2020). Participants answered the questions in the scenario by writing explanations and drawing causal loop diagrams. The researcher transformed the written responses into causal loop diagrams following the method developed by Kim and Andersen (2012) and analyzed the causal loop diagrams that the participants had already drawn. The results show that participants' mental model representations derived from their explanations focused on linear relationships and ignored feedback. When participants were asked to draw causal loops, most were able to incorporate feedback loops into their mental model representations, which made a more complex structure. This study suggests that causal loop diagrams need to be integrated into instructional practices to initiate the development of complex mental models.

ÖZET

ÖĞRETMEN ADAYLARININ İKLİM DEĞİŞİKLİĞİ TEMELLİ BİR VAKA SENARYOSUNA İLİŞKİN ZİHİNSEL MODELLERİNİN SİSTEM DÜŞÜNCESİ YAKLAŞIMIYLA İNCELENMESİ

İklim değışikliğı dinamik yapısı ve etkileşimleri nedeniyle karmaşık sorunlardan biridir. Ancak insanlar basit ve doğrusal zihinsel modellere sahip olma eğilimindedir. Bu nedenle, iklime bir sistem olarak yaklaşmak ve iklim değışikliğini ele almak için basit zihinsel modellerin ötesine geçmek gerekir. Eğitimin rolü göz önüne alındığında, öğretmenlerin ve öğretmen adaylarının sistem düşüncesi konusunda yetkin olmaları gerekmektedir. Bu çalışma, öğretmen adaylarının iklim değışikliğı temelli bir vaka senaryosuna ilişkin zihinsel modellerini sistem düşüncesi yaklaşımı ile incelemektedir. Veriler, bir devlet üniversitesinde iklim değışikliğı eğitimi dersine kayıtlı öğretmen adaylarından Davis ve diğerleri (2020) tarafından geliştirilen Urmiye Gölü Vinyeti aracılığıyla toplanmıştır. Katılımcılar senaryodaki soruları açıklama yazarak ve nedensel döngü diyagramları çizerek yanıtlamışlardır. Araştırmacı Kim and Andersen (2012) tarafından geliştirilen yöntemi izleyerek yazılı yanıtları nedensel döngü diyagramlarına dönüştürmüştür ve katılımcıların çizmiş olduğu nedensel döngü diyagramlarını analiz etmiştir. Sonuçlar, katılımcıların açıklamalarından türetilen zihinsel model temsillerinin doğrusal ilişkilere odaklandığını ve geri beslemeyi göz ardı ettiğini göstermektedir. Katılımcılardan nedensel döngüler çizmeleri istendiğinde, çoğu geri besleme döngülerini zihinsel model temsillerine dahil edebilmiş ve bu da daha karmaşık bir yapı oluşturmuştur. Bu çalışma, karmaşık zihinsel modellerin gelişimini başlatmak için nedensel döngü diyagramlarının öğretim uygulamalarına entegre edilmesi gerektiğini göstermektedir.

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LIST OF ACRONYMS/ABBREVIATIONS

CLDs	Causal Loop Diagrams
WCI	Web-like Causality Index



1. INTRODUCTION

In recent years, the world has been experiencing a series of environmental, socio-economic, technological and geopolitical crises, including biodiversity loss, collapse of ecosystems, global climate change, energy and food shortages, economic disruption and health problems (World Economic Forum, 2023). These problems are complex, ambiguous, and interrelated. People have mental models to understand and make decisions about such complex problems. Forrester (1971) defined mental models as systemic representations of the world, Meadows *et al.* (1974) as conclusions drawn from observations of real events, and Senge (1990) as generalizations or visualizations that express our understanding and perception of the world in the deep recesses of our minds. However, the mental models people develop for complex problems are not always complicated and tend to deal with relationships in a linear way without feedback and time delays (Meadows, 2008; Sterman, 1994).

It may not be possible to understand and deal with complex problems with a wide range of effects from a narrow and simple perspective. Broad and holistic perspectives and approaches that focus on educating individuals as global citizens are needed for a society that is prepared to deal with complex challenges (Sterling, 2008). In this context, Education for Sustainable Development has included systems thinking among the eight key competencies for dealing with today's complex challenges, defining it as the ability to deal with uncertainty and understand complexity (UNESCO, 2017; 2021). Systems thinking provides a holistic approach to understand complexity and fortunately, there are several studies that promote students' systems thinking skills (e.g., Ben Zvi Assaraf and Orion 2010; Evagorou *et al.*, 2009; Mambrey *et al.*, 2020). With systems thinking, individuals gain the ability to see how to approach a system problem, the content of a system, how it is organized, and the behavior of the systems from a holistic framework (Arnold and Wade, 2017).

There are a number of ways that have been developed to understand the behavior and dynamics of a system, including modeling and simulation techniques. In the literature, methods have been used to represent mental models in different ways, such as causal maps, causal loop diagrams (CLDs), and cognitive maps which are used to create system models (Capelo and Dias, 2009; Gray *et al.*, 2019). Creating causal diagrams of a system provides testing and communication for understanding the structure and behavior of the system and activates mental models in decision-making processes. Simulation of mental models allows inferences to be made about the future behavior of the system (Capelo and Dias, 2009). Using mapping techniques helps to develop deep understanding of complex systems (Gray *et al.*, 2019).

Mapping complex systems, which enables the development of a common understanding among individuals, sheds light on how causal relationships arise (Aminpour *et al.*, 2022; Wasserman and Banks, 2017). Causality is shown in cognitive maps in different patterns such as; a simple pair of cause and effect, a laundry list of causes (or effects), chain(s) of causes and effects and circular chain(s) of causes and effects. The circular chain structure illustrates feedback loops and interdependencies between causes and effects (Haque *et al.*, 2023). In some studies in the literature, participants' mental models were revealed by mapping their written statements by the researchers (Haque *et al.*, 2023; Kim and Andersen, 2012), or participants were actively involved in a modeling process like creating causal loop diagrams and causal maps (Cox *et al.*, 2018; Plate, 2010).

In the current study, the representations of pre-service teachers' mental models of a complex socio-environmental problem based on global climate change was examined. Teachers have some misconceptions and limited understanding of complex issues such as climate change due to its nature and the fact that it is not an easily communicated topic (Liu *et al.*, 2015; Moser, 2010). Therefore, preparing teachers to teach climate change is an important issue for teacher preparations (Beach, 2023). In this context, to examine the mental models of pre-service teachers on climate change, their written explanations were examined and visualized from by researchers. Also, the complexity

level of the pre-service teachers' representations of the same problem with causal loop diagrams, one of the system dynamics tools, were explored. Thus, the understanding of pre-service teachers about a complex system was compared in terms of written and drawn representations, and it was investigated whether there is a difference in their understanding complexity between written and drawn representations.

1.1. Purpose of the Study

The aim of this study is to examine the mental models of preservice teachers on a climate change-based case scenario with the systems thinking approach.

1.2. Significance of the Study

Global climate change is one of the most complex problems in the world today due to its dynamic nature and the interactions between the components of climate systems. It is characterized by many positive and negative feedback, delays in actions over time, and irreversibility of the consequences of actions (Sterman and Sweeney, 2002). Systems thinking is an approach to understanding complexity and revealing the underlying structure of a system (Shaperdson *et al.*, 2012; Sterman, 2000). People's limited mental models are more prone to single-cause thinking and people have difficulty in perceiving complex problems, at this point, systems thinking is very important for eliciting mental models (Hmelo-Silver *et al.*, 2007; Senge, 1990).

Examining the mental models of pre-service teachers who educate students as future decision makers can shed light on the impact on students' decision-making processes for future problems. Individuals with high content knowledge may still have difficulty in understanding complex systems, which shows that the solution is not to acquire more knowledge, but to gain a systems thinking perspective (Sterman, 2011; Sweeney and Sterman, 2007).

Students should be given opportunities to interact with system dynamics tools. This can improve their understanding of complex systems and help them better recognize cause-effect relationships and feedback (Doganca Kucuk and Saysel, 2018). Causal loop diagrams are important for understanding the structure of systems and for eliciting mental models (Haraldsson, 2004). Many studies have examined students' interaction with systems thinking tools, but studies with teachers and pre-service teachers are limited (Lee, 2015). This study aimed to contribute to the literature of systems thinking in education due to the limited number of studies with pre-service teachers.

Another significance is that this study revealed how pre-service teachers can visualize their mental models by using system dynamic tools. Many studies in the literature have used different methods for mapping mental models, such as causal map, concept map, causal loop diagrams (Cox *et al.*, 2019; Haque *et al.*, 2023; Plate 2010, Tripto *et al.*, 2013). From a systemic perspective, it can be considered that causal loop diagrams are one of the tools that model the underlying structure and behavior of systems. Based on this idea, causal loop diagrams have been the focus of the current study to visualize pre-service teachers' mental models. As a result, how a complex socio-environmental scenario based on global climate change is perceived by pre-service teachers was revealed through written and drawn representations.

This study has shown empirical results by comparing written and drawn representations, reflecting our mental models through different forms of expression. There are examples in the literature comparing different forms of expression to understand complexity (Gobert and Clement, 1999; Schmidt *et al.* 2024). This study emphasized to encourage the use of these different ways to express our mental models for understanding complex systems. In this study, participants' mental models based on their drawn causal loop diagrams were found to be more complex than mental models based on their writing explanation. More research is needed on how our ways of expression affect our mental models. Also, further investigations were needed to show the impact on causal loop diagrams on the ability to express our mental models.

This study introduced an interdisciplinary approach to environmental education for pre-service teachers from diverse backgrounds based on systems thinking. The findings can inform the development of course content and curricula, as well as highlight the importance of practical applications, such as modeling, in learning complex systems.

1.2.1. The Research Questions

In this study, the following questions were examined.

- (i) What are the preservice teachers' mental models on climate change-based case scenarios?
- (ii) What is the level of complexity of preservice teachers' causal loop diagrams on climate change-based case scenarios?
- (iii) To what extent do systems complexity of preservice teachers' written explanations and causal loop diagrams on climate change-based case scenarios differ?

1.3. Definitions of Key Terms and Concepts

This section is divided into two parts: conceptual definitions and operational definitions.

1.3.1. Conceptual Definitions

- Systems thinking: "Systems thinking is a group of synergistic analytic skills which are utilized to increase the capableness of specifying and comprehending systems, anticipating their behaviors, and inventing modifications to them for generating desired influences. These skills perform as a system together" (Arnold and Wade, 2015, p. 675).
- Complexity: Sterman (2002) defined complexity as "the number of, or links among, the elements of a system, or the dimensionality of a search space" (p. 5). Complexity of the world limits people's understanding and affects their decision-

making. The ability to understand the long-term effects of decisions and find solutions is linked to an understanding of mental models and, ultimately, the complexity of systems (Sterman, 2000). Sterman (2001) attributes the resistance in our decision-making processes to the unpredictable behavior or unintended consequences of interacting parts in systems over time, called dynamic complexity. Dynamic complexity has been associated with stocks and flows, feedbacks and time delays (Sterman, 2001).

- **Mental Models:** The concept of mental models was defined in similar ways by systems thinking researchers. Forrester (1971) defined mental models as "mental images in one's head" (p. 112). Likewise, according to Senge (1990), mental models are "internal images of how the world works" (p. 174). To elicit and explain individuals' mental models of complex systems, cognitive tools are needed to visualize the structure and inter-causality of the system (Hung, 2008; Lane, 2008).
- **Recognizing Interconnections:** The ability to see the connections that exist between the components of a system, which is also considered a fundamental level of systems thinking (Arnold and Wade, 2015; Stave and Hopper, 2008).
- **Identifying and Understanding Feedback:** The ability to identify cause and effect relationships between components of a system, to identify causal loops, to understand how feedback mechanisms are formed, and to determine the polarity of feedback loops (Arnold and Wade, 2015; Stave and Hopper, 2008). Feedback is a specialized term for system dynamics and is different from the general meaning of criticism (Sweeney and Sterman, 2007).

1.3.2. Operational Definitions

In the present study, participants' systems thinking was measured focusing on understanding complexity regarding following measures.

- **Variables (Node):** In a causal map, what is expressed in words (in the form of nouns) are the variables of the map, called nodes.

- Links: Links are represented by arrows in a causal loop diagram.
- Link Density: A measure of interconnectedness and is calculated as the ratio of links (edges) to nodes in a map (Haque, 2023; Plate, 2010).
- Web-Like Causality: It is calculated as the ratio of branching nodes to total nodes in the map. There are two types of branching nodes: nodes with more than one cause (in arrows) and nodes with more than one effect (out arrows) (Haque, 2023; Plate, 2010).
- Feedback Density: A measure of feedback loops is calculated as the fraction of edges and nodes in the map that are involved in at least one feedback loop (Haque 2023; Naugle *et al.*, 2023).
- Cyclomatic Complexity: A measure of complexity in terms of separate connected components, is calculated as the number of links subtracted by the number nodes added to two times the number of connected components (Haque 2023; Naugle *et al.*, 2023).
- Causal Complexity: A measure of complexity in terms of separate connected components and feedback loops, is calculated with formula: Cyclomatic Complexity * (1 + Feedback Density) (Haque 2023; Naugle *et al.*, 2023)

2. LITERATURE REVIEW

2.1. System and Systems Thinking

Meadows (2008) defined a system as a set of interconnected elements organized in such a way as to achieve something and emphasizes three key features of a system: elements, interconnections, and function or purpose. Dori *et al.* (2019) presented a definition intended to encompass various system worldviews. According to this definition, a system is a collective behavior or meaning produced by components or parts that exhibit behaviors or meanings they cannot exhibit on their own (Dori *et al.*, 2019).

According to Bar-yam (2002), complex systems are defined as an approach that examines the effect of parts on holistic behavior and the interaction and relationships of the system with its environment. Understanding complex systems is the foundation of science. The complexity of the system makes it difficult to understand systems because of the dynamic interactions at many levels. This makes it important to create clearer representations of systems. Systems thinking is seen as a solution to better understand complex systems, which means seeing the world as a complex system and understanding that everything interacts with each other (Senge, 1990). This approach allows us to see the world from a holistic perspective, to create system representations more clearly and to understand complex systems (Hmelo-Silver *et al.*, 2007; Sterman, 2000).

There has been no consensus on a common definition of systems thinking (Stave and Hopper, 2007). Since Richmond (1994), who coined the term systems thinking, the definitions of systems thinking have been revised. Senge (1990) defined systems thinking as a discipline to see the whole rather than the parts, to see interconnections, and to focus on change. Meadows (2008) saw systems thinking as a way to better understand a complex and interconnected world, because it allows us to focus on the parts and interdependent relationships, question the impact of our behavior on the

future, and be more creative and courageous. Stave and Hopper's (2008) comprehensive review found that the most common characteristics of systems thinking are grouped into seven categories: recognizing interconnections, identifying feedback, understanding dynamic behavior, differentiating types of flows and variables, using conceptual models, creating simulation models, and testing policies.

In addition, according to Arnold and Wade (2015), the definitions in the literature were discussed in some aspects, and it was argued that systems thinking should be defined in three main aspects: elements, interconnections, and a goal or function. It was emphasized that although many definitions in the literature are inadequate in this regard, they have important common points. These commonalities are: interconnections, understanding dynamic behavior, system structure as a cause of that behavior, and the idea of seeing systems as whole rather than parts (Arnold and Wade, 2015; Richmond, 1990; Senge, 1990; Stave and Hopper, 2008).

By reviewing all the definitions, Arnold and Wade (2015) approached systems thinking from a systems perspective and created a systemigram, expressing systems thinking in terms of the interconnections between the eight components. In the systemigram, the important eight components are: recognizing interconnections, identifying and understanding feedback, understanding system structure, differentiating types of stocks, flows, variables, identifying and understanding non-linear relationships, understanding dynamic behavior, reducing complexity by modeling systems conceptually, and understanding systems at different scales. There is no hierarchy between the components, and each component contributes to the development of systems thinking (Arnold and Wade, 2015).

2.2. System Dynamics Tools and Iceberg Metaphor

To improve understanding and dealing with complex systems, system dynamics tools are capable of capturing feedback processes, stocks and flows, time delays, and other dynamic complexity processes (Sterman, 2001). Commonly used tools include

behavior over time graphs, stock-flow diagrams, causal loop diagrams, the ladder of inference (Doganca Kucuk and Saysel, 2018). The Iceberg Model is a metaphor that visualizes a system in 4 layers: events, models, structure, and mental models. Mental models at the invisible bottom layer of the iceberg influence the structure of the system. Structure creates behaviors, patterns and trends. Events are the visible part of the iceberg at the top. The iceberg model is an important metaphor that provides a holistic perspective by incorporating system dynamics tools (Göktepe, 2022; Senge, 1990).

- (i) Behavior Over Time Graphs: Behavior over time graphs are used to show the change of variables over time; for example, weight and number of customers can be represented in these diagrams. Indicators such as rapid increase or decrease symbolize a reinforcing process, while oscillation symbolizes a balancing process (Kim, 1999). Behavior over time graphs capture current behavioral patterns but are insufficient to grasp the underlying structure of the system's behavior (Senge, 1990).
- (ii) Stock-Flow diagrams: Stock-flow diagrams were considered a detailed frame for the systems (Lane, 2008). Stocks are defined as things that accumulate over time and can be measured over a time interval, e.g., the amount of water in the bathtub, population, savings; and flows are defined as things that change over time, such as, the rate of inflation, etc. (Kim, 1999).
- (iii) Causal Loop Diagrams: Causal loop diagrams are used as systems thinking tools that map the structure of the system and feedback to understand feedback and how behavior manifests itself in the system (Haraldsson, 2004). Senge (1990) highlighted the importance of the transition from linear to feedback thinking for understanding complexity, therefore causal loop diagrams are considered as effective tools for representing feedback thinking (Lane, 2008). Three basic elements make up a causal loop diagram: nodes, links, and feedback loops. Nodes are variables in the system and are expressed by nouns. These nouns must be able to change in an ascending or descending manner. Links represented by arrows drawn from one node (variable) to another indicate causality. A link marked with a (+)

sign, or the letter S represents a change in the same direction. For example, as variable A increases, variable B increases and vice versa. A link marked with a (-) sign, or the letter O represents a change in the opposite direction. For example, variable A increases while variable B decreases or vice versa (Barbrook-Johnson and Penn 2022; Lane, 2008). The presence of feedback loops makes causal loop diagrams special, and curved arrows make feedback loops look better on a diagram (Barbrook-Johnson and Penn, 2022). Feedback is an action within a system that causes an effect that feeds back into the system itself. In other words, cause and effect are intertwined in feedback (Haraldsson, 2004). A system can involve the interaction of two types of feedback mechanism, positive (reinforcing) loops and negative (balancing) loops. Positive loops ensure the growth and maintenance of behaviour in the system, while negative loops counteract behaviour in the system (Sterman, 2001) The letter R is used to show the (positive) reinforcing loop and the letter B is used to show the (negative) balancing loop (Lane, 2008).

- (iv) The Ladder of Inference: The Ladder of Inference is a tool that reveals the mindset between actual observations and actions when making decisions (Senge, 1990). Many studies in the literature emphasize the importance of system dynamics tools to help represent mental models of groups or individuals and develop systems thinking skills (Doganca Kucuk and Saysel, 2018; Hung, 2008). In a study conducted by Hung (2008) with university students participated in the processes of behavior over time graphs, stock-flow diagrams, and dynamic simulation models, respectively, and created a causal loop diagram and simulation model on a problem they chose as a project task. As a result, it was found that there was an increase in students' interconnections, cause-effect relationships and feedback processes in causal loop diagrams (Hung, 2008).

Similarly, a systems-based education content was prepared for seventh-grade students on dynamic environment topics, including activities such as causal loop diagrams, stock flow diagrams, and creating simple dynamic models on STELLA (a modeling software) with seventh-grade students (Doganca Kucuk and Saysel, 2018) It was shown that system dynamics tools are encouraging tools for students to understand system

concepts and engage with dynamic environment issues (Doganca Kucuk and Saysel, 2018) In another study, systems dynamics were considered as essential tools that offer a systems thinking perspective outlook in policy and decision-making procedures that align with societal concerns and goals of sustainable development (Strapasson *et al.*, 2022).

In the current study, pre-service teachers drew causal loop diagrams to visualize their mental models, thus gaining a comprehensive understanding of complexity in terms of recognizing interconnections and identifying and understanding feedback.

2.3. Systems Thinking in Education

Many studies have shown that it is difficult to understand complex systems (Evagorou *et al.*, 2009; Hmelo-Silver *et al.*, 2007) While the idea that children are natural systems thinkers is widely accepted, an important question is how schooling influences them in an increasingly complex world. Many educators support integrating systems thinking and concepts into the school curriculum (Sweeney and Sterman, 2007). Systems thinking plays an important role in various educational fields, including biology (Fanta *et al.*, 2020; Glissen *et al.*, 2020; Tripto *et al.*, 2017), chemistry (Delaney *et al.*, 2021; Szozda *et al.*, 2022; York and Orgil, 2020), physics (Rakbamrung *et al.*, 2015), geography (Cox *et al.*, 2019), engineering (Lavi and Dori, 2020), and environmental education, especially on topics such as global climate change, ecosystems, and sustainability (Demssie *et al.*, 2023; Feriver, 2022; Karaarslan Semiz and Teksöz, 2019; Liu, 2023; Shepardson *et al.*, 2014).

Concepts such as ecosystem, global climate change or processes such as water cycle, rock cycle, etc., are difficult to understand due to their complex and dynamic nature, and it is not easy to understand the relationships between parts of the system and feedback mechanisms (Sweeney and Sterman, 2000; 2007, Fanta *et al.*, 2020) There were different studies supporting this in the literature (e.g., Ben Zvi Assaraf and Orion, 2005; 2010; Sheparrdon *et al.*, 2014; Sibley *et al.*, 2007). Mambrey *et al.* (2020)

examined fifth and sixth-grade students' systems thinking level on food chains. It was concluded that students are able to produce single-cause solutions and ignore other components of the system and feedback loops. Similarly, studies in the topics such as the water cycle, the carbon cycle and the rock cycle were found that students tended to think in parts and failed to understand hidden dimensions (Ben Zvi Assaraf and Orion, 2005; Sibley *et al.*, 2007). Furthermore, considering the concept of climate as a system, Shepardson *et al.* (2014) presented a model of seventh-grade students' understanding of climate as a system; in this model, students' conceptualization of climate is based on cause-effect relationships without considering feedback loops.

The acquisition of a systems thinking perspective offers a viable solution for understanding complexity (Stermann, 2000). Therefore, it is stated that it is very important to start systems thinking education at an early age (Evagorou *et al.*, 2009). Another study by Feriver (2020) supported this view and showed that when preschool students were exposed to systems thinking interventions, they improved their definitions of systems and were able to see the invisible parts of the system. It is supported that systems thinking makes gains through courses in which curriculum is implemented (Liu *et al.*, 2023). Ben Zvi Assaraf and Orion (2005) found that by integrating concept maps, drawings and outdoor experiences, students exhibited a shift towards holistic thinking. In a similar study with fourth-grade students, Ben Zvi Assaraf and Orion (2010) showed that students developed systems thinking and emphasized the importance of teaching systems thinking at an early age. It was found that outdoor activities in which students engage in concrete interactions are more likely to enable students to develop a more abstract mental model of the interrelationships within and between earth systems (Ben Zvi Assaraf and Orion 2010).

To adapt to a rapidly changing world, students need to be raised as systems thinkers who understand the complexity of systems. Therefore, they should receive specialized education under the guidance of qualified teachers (Rosenkränze *et al.*, 2017). Karga and Ceyhan (2024) found that teachers' systems thinking and system dynamics approach needs to be improved with teacher training programs, workshops,

etc. These findings indicated that research with pre-service teachers should be a priority, but research with pre-service teachers has been limited in the literature (Bielik *et al.*, 2023).

In a study, Lee *et al.* (2019) found that pre-service teachers struggled with describing system components and processes, identifying multiple relationships within systems and subsystems, identifying hidden dimensions of the system, and understanding human influences on the system. Similar results have emerged that teachers have difficulty in making connections between relationships (Ateşkan and Lane, 2018; Karaarslan Semiz and Teksöz, 2019). However, Karaarslan Semiz and Teksöz (2019) stated that there is hope that an education integrated with outdoor activities for sustainable development courses will improve pre-service teachers' systems thinking.

The current study explored the mental models of pre-service teachers who received the climate change course in one semester towards a complex socio-environmental problem and measured their understanding of complexity by analyzing their mental models extracted from written explanations and causal loop diagrams.

2.4. Measuring Systems Thinking

In the literature, various methods such as self-reporting, scenario-based assessments/ scenarios and mapping have been applied to measure systems thinking (Dugan *et al.*, 2022). Self-reporting is students' self-assessment (Davis *et al.*, 2023; Davis and Stroink, 2015; Thibodeau *et al.*, 2016). According to the study by Davis *et al.* (2023), there was no significant relationship between self-report assessments and scenario-based assessment methods. Therefore, the limitations of self-report assessments need to be considered when using them as an assessment tool for systems thinking competence (Davis *et al.*, 2023).

Another method is scenario-based assessments/case scenarios using rubrics (Davis *et al.*, 2020; Dorani *et al.*, 2015; Grohs *et al.*, 2018). The important feature of scenario-

based assessments is that they are designed in the context of a realistic problem and include open- and closed-ended questions (Norris *et al.*, 2022). Grohs *et al.* (2018) developed a case-based scenario to examine systems thinking in higher education based on a community problem scenario in the framework of problem, perspective, and time. Students' responses were analyzed according to a scoring rubric under the headings of problem identification, information needs, stakeholder awareness, goals, unintended consequences, implementation challenges, and alignment (Grohs *et al.*, 2018). Similarly, Davis *et al.* (2020) developed a scenario about a socio-environmental problem. In this scenario, students were expected to identify the problem and the relationships with the problem given in the scenario and propose solutions. This scenario was designed to analyze students' ability to recognize variables and their relationships and feedback loops. Students' written responses were represented as word arrow diagrams and scored using a rubric (Davis *et al.*, 2020).

Haque *et al.* (2023) extended the study using the same scenario developed by Davis *et al.* (2020) and used systems thinking to visualize mental models. Haque *et al.* (2023) transformed students' mental models about a socio-environmental problem into network representations by extracting them from written answers following Kim and Andersen's (2012) method of transforming qualitative data into causal loop diagrams. Similar structural metrics in the literature (link density, web-like causality index (WCI), feedback density, cyclomatic complexity, and causal complexity) was used to compare network representations as mental models (Haque *et al.*, 2023).

Constructing maps is another way to assess system thinking abilities of individuals or groups (Cox *et al.*, 2018; 2019; Plate, 2010). In the mapping format, participants are asked to participate in creating a visual representation. Words can be found and associated with shapes like arrows, etc., in this visual representation. (Dugan *et al.*, 2022). In the literature, mapping activities can be associated with causal loop diagrams, causal maps, causal structure diagrams, etc. The term causal loop diagrams were preferred mostly in the System Dynamics field (Sterman, 2000).

In the study of Plate's (2006), students were asked to read a short article about a complex environmental problem and then, as a class activity, to create a causal map using the concept cards given to the students. Students' causal maps were analyzed according to their structural features like, the web-like causality index and link density to examine interconnectedness. (Plate 2006).

Another study with university students from different disciplines investigated how students' systems thinking about obesity would change when supported by a computer-based causal loop diagram. Students received systems thinking training for two weeks. Causal loop diagrams related to obesity were created by the students and they had the opportunity to revise the diagrams at three different time intervals. Thus, students addressed the obesity problem by using causal loop diagrams and proposed solutions to this situation (Leung *et al.*, 2024). The causal loop diagrams were compared regarding the presence of components, relationships, interconnectedness as measured by the web-like causality index, feedback loops, and actions proposed (Leung *et al.*, 2024).

In a study conducted by Cox *et al.* (2019), systems thinking was assessed in scenarios and mapping activities. Students were asked to read two scenarios and then answer questions related to the scenarios. Based on the information provided in the scenarios, students created causal diagrams. The results were discussed in terms of identifying relationships between different variables and describing the nature of the relationships.

In another study, Naugle *et al.* (2023) compared causal structure diagrams for understanding complexity through three criteria which were cyclomatic complexity, feedback density, and causal complexity. Naugle *et al.* (2023) introduced two new criteria for measuring model complexity by emphasizing the importance of feedback and considered feedback as a fundamental component of models. Since cyclomatic complexity ignores the feedback loops in the map, a new concept, feedback density, was introduced, which emphasizes the necessity of feedback thinking. Furthermore, causal complexity was introduced by combining feedback density and cyclomatic complexity.

On the other hand, in the literature, there are examples of studies in which participants were not directly involved in mapping activities, but researchers analyzed qualitative data from a systems thinking perspective. Researchers have transformed qualitative data such as interview transcripts and open-ended questions into causal loop diagrams (Kim and Andersen, 2012; Owen *et al.*, 2018). Compared to traditional methods, it has been argued that causal loop diagrams are effective in illustrating feedback and thus providing an understanding of future outcomes (Owen *et al.*, 2018).

In the current study, to explore the participants' mental models through a scenario, the researchers tried to convert the written texts into causal loop diagrams, and the participants had the opportunity to create their own causal loop diagrams. The causal loop diagram as a mapping activity was used as a tool to explore the mental models of pre-service teachers. The pre-service teachers were expected to read a scenario about global climate change and answer questions both in writing an explanation and by drawing causal loop diagrams. Students written explanations were transformed into causal loop diagrams by the researchers. Also, participants were actively involved in creating their own causal loop diagrams to answer the same questions. Overall, the representations of mental models provided by the pre-service teachers through writing and drawing were visualized from a systems thinking perspective. The complexity of the participants' mental models analyzed through both writing and causal loop re was examined and it was determined whether or not there was a difference.

There were studies in the literature that examined the effect of different tasks. In one study, students showed a better understanding of the causal and dynamic aspects of a particular domain in a diagramming task compared to a summary writing task (Gobert and Clement, 1999). Another study examined the difference between explanation writing and diagramming task in terms of understanding causal and dynamic aspects. Since writing explanations requires more thinking skills, no difference was found with diagramming, which is an important finding because different learning tasks can have a significant impact on the elicitation of mental models (Gobert, 2005).

It is important to examine the impact of different ways for eliciting dynamic processes. Therefore, this study compared how mental models expressed in two different ways (both by writing and causal loop diagrams).

In the literature, it was indicated that diagramming, like causal maps, and causal loop diagrams, are more likely to have non-linear and systemic features than written texts which tend to be associated with a linear structure (Lane, 2013). In a study of McCrudden *et al.* (2007), students who read a text presented with a pre-prepared causal diagram were found to understand causal relationships better than students who read the text without any causal diagram. This finding showed that causal diagrams help students construct causal relationships and make explicit implicit causal relationships in the given text (McCrudden *et al.*, 2007). It was indicated that causal diagrams are effective tools and proposed to investigate at what they contribute to the understanding of implicit causal relationships in the given text. However, students had difficulty in establishing causal relationships even with ready-made diagrams (McCrudden *et al.*, 2007). Cox *et al.* (2018) suggested developing new teaching strategies and offering methods that make students active such as diagramming in the classroom. Rather than presenting pre-prepared diagrams, giving students the opportunity to construct their own diagrams contributed to their understanding complex relations (Jonassen and Ionas, 2008; Shin and Jeong, 2021). Therefore, it is important to engage students with diagramming practices (e.g. causal maps, and causal loop diagramming). Plate (2010) proposed that causal maps serve as a valuable tool for gaining insight into the dynamic nature of system structure, thus enabling a shift away from linear causality. Also, there was evidence of a positive impact on students' systems thinking through diagramming as a group activity. Leung *et al.* (2024) found that as a group, constructing and revising causal loop diagrams was effective in students' decision-making processes and also enabled them to recognize missing parts. Thus, students could gain a holistic approach to seeing different aspects of the system (Cox *et al.*, 2018).

One of the most important practices of systems thinking is using diagrams. However, a review of the existing literature reveals a limited number of studies on diagram-

ming and teaching and learning how to integrate diagrams (Lane, 2013). Therefore, causal loop diagrams are the focus of this study as a systems thinking practice. Causal loop diagrams provide a good starting point for understanding the structure and behavior of systems. This tool allows individuals and groups to visualize their ideas and mental models, think critically about and discuss connections and loops. Also, it was easy to access, as it required only basic drawing skills, a pencil, and a paper (Lane, 2008).

2.5. Climate System and Global Climate Change

From an ecological perspective, climate is a system of five components: atmosphere, oceans, land, life (plants and animals), and ice (Ruddiman, 2001). In addition, humans can be considered as part of this system and there is evidence that human activities affect the climate system. 1.1°C increase in global surface temperature between 2011 and 2020 compared to 1850-1900 has been shown to be caused by greenhouse gas emissions from human activities (IPCC, 2023). It is known that the Earth's climate has been changing for decades and is driven by different factors, but it is clear that the main driver of global climate change is the release of greenhouse gasses as a result of human activities, which can be defined as human-induced global climate change. Global climate change is defined by the IPCC as a change in the climate that can be characterized (e.g., using statistical tests) by changes in its variability, typically over a period of decades or more (IPCC, 2014). When global climate change is considered as a system, it is seen as changes that occur through components that are thought to interact with each other and through feedbacks in the interaction between these components. Likewise, these changes can lead to long-term changes and cause temporal and spatial lags. It is crucial to view climate as a system from a holistic perspective to effectively understand how the stock-flow structure is built, how feedback mechanisms are processed and the impact of delays, and how they affect the whole system (Shepardson *et al.*, 2014, Sterman and Sweeney, 2002). Therefore, global climate change is a systemic issue due to the complexity of climate dynamics.

Understanding what global climate change means to students and teachers is important because research shows that both teachers and students have misconceptions about the topic (Liu *et al.*, 2015). They may also be influenced by their personal experiences, such as where they live or their culture (Kahan *et al.*, 2011). In addition, challenges such as the invisibility of causes, distant impacts, uncertainty, and lack of understanding of human impacts on climate change make it difficult to communicate the issue (Moser, 2010).

When the literature is examined, global climate change was most embedded within disciplines such as biology, environmental sciences, and earth sciences (Bhattacharya *et al.*, 2021). According to the results, in general, it is evident that teachers avoid emphasizing the social, political, and economic aspects of climate change. They addressed global climate change as general concepts of science courses such as greenhouse gas effect, carbon cycles, biodiversity, weather and climate, and sea level (Dawson, 2012, Herman *et al.*, 2017, Plutzer *et al.*, 2016). However, in today's complex world, it is necessary to approach climate change education from a holistic perspective to understand all aspects affecting the climate system (Shepardson *et al.*, 2014; Sterman and Sweeney, 2007). Studies approaching climate change education from a holistic perspective have increased after the 2000s (Bhattacharya *et al.*, 2021). Similarly, Rousell and Cutter-Mackenzie-Knowles (2020) argued that instead of focusing on the lack of scientific knowledge about climate change, an interdisciplinary approach should be taken by addressing the emotional dimensions of climate change so that students can be empowered to mitigate climate change. Therefore, it is important to prepare students to make the right decisions about how to address climate change, especially in the social dimension with learning and teaching practices (Stevenson, 2017). In literature, creating learning environments where students can actively engage and discuss climate change concepts and experience possible impacts through local examples are the most commonly suggested ways to teach about climate change. These include field trips, interviews, worksheets, data collection, project work, etc. (Monroe *et al.*, 2019) In the current study, the systems thinking approach was suggested as a holistic approach to understanding the complexity of climate change.

3. METHODOLOGY

This section provides detailed information about the research design, participants, data collection tools, procedure, and data analysis.

3.1. Research Design

This research was an exploratory case study design that aims to answer three research questions in depth. Exploratory case studies aim to answer “what”, and “how” questions in depth while building a theory (Yin, 2014). The current study addressed the following questions.

- (i) What are the pre-service teachers’ mental models on climate change-based case scenarios?
- (ii) What is the level of complexity of preservice teachers’ causal loop diagrams on climate change-based case scenarios?
- (iii) To what extent do systems complexity of preservice teachers’ written explanations and causal loop diagrams on climate change-based case scenarios differ?

3.2. Participants and Context

The purposive sampling method was used to select participants because they were selected based on a specific criterion. This criterion was that they were taking the Climate Change Education course in the spring semester of 2023-2024. This was an important criterion because this course allowed them to consider the climate as a system, familiarize themselves with the concepts of systems thinking and system dynamics tools, and gain experience in drawing causal loop diagrams.

Therefore, the participants of this study were 39 preservice teachers who were enrolled in the Climate Change Education course in the spring semester of 2023-2024

at a public university. This was an elective course, and the participants had voluntarily agreed to take place in the study.

The participants were grouped for data collection, with 18 groups formed with a maximum of three individuals to provide collaboration. They had the opportunity to share their ideas to reflect and activate their mental models. However, the data from one group were excluded from the study due to technical issues. In particular, the Word document file of this group could not be opened. The attempts to access the data were unsuccessful. As a result, data from 17 groups were included in the analysis (N=36).

Demographic information about participants' gender, GPA, department, and whether they had taken courses on climate/climate change and systems thinking was shown in Table B.1. There were 27 female and 9 male preservice teachers who participated in this study.

Table 3.1. Demographic information about the participants.

Demographic Criteria	Categories	Frequency
Gender	Female	27
	Male	9
GPA	2.5 – 2.9	17
	3.0 – 3.4	12
	2.0 – 2.4	6
	3.5 – 4.0	1
Departments	Primary Mathematics Education	16
	Primary Science Education	14
	Secondary Mathematics Education	3
	Secondary Chemistry Education	1
	Guidance and Psychological Counseling	1
	Preschool Education	1

Table B.1 Demographic information about the participants. (cont.)

Demographic Criteria	Categories	Frequency
Taking a course about climate/climate change	No	19
	Yes	17
Taking a course related to systems thinking	No	22
	Yes	14

While 17 of the pre-service teachers indicated that they had previously taken a course on climate and climate change, 19 indicated that they had not. In addition, 14 of the pre-service teachers indicated that they had taken a course on systems thinking, while 22 indicated that they had not. For example, the ESDx 101 and 201 courses were mentioned by the pre-service teachers. ESDx 101 is an online course that introduces systems thinking and systems dynamics tools, while ESDx 102 is an online course that introduces systems thinking specifically in climate change. However, these courses were first introduced in the course Climate Change Education, with ESDx 101 in particular expected to be completed during the course.

Table B.1 shows data from 36 pre-service teachers in different departments was examined in this study. However, the majority of the preservice teachers come from the field of science and mathematics education. There were 14 preservice teachers in primary science education, 16 in primary mathematics education, three in secondary mathematics education, one in secondary chemistry education, one in guidance and counseling, and one in preschool education.

The course has been designed to be inclusive of preservice teachers from a range of disciplines. The main reason why students from all departments of the Faculty of

Education can enroll in this course is that climate change is a complex global problem that requires an interdisciplinary perspective.

Table 3.2 shows the outline of the course over a 14-week period. The first week introduced the definition of systems, the importance of systems thinking and systems thinking practices. In the following weeks, the earth system was discussed under 3 main headings: land system, water system and air system. The course focused on the scientific dimension of the climate system but also emphasized the social and economic aspects. For this reason, the effects of population dynamics, consumption, wealth and emissions on the climate system were discussed using system dynamics tools. Greenhouse gas effect, and carbon dynamics (bath-tub dynamics) were discussed through stock-flow diagrams and causal loop diagrams. To provide a holistic approach, the Interconnected Systems activity emphasizes the interconnectedness and interaction of all systems.

Active participation was important throughout the course. Classroom activities included group discussions, whole class discussions, and simulation games (C-ROADS and EN-ROADS Climate Solutions Simulator). For assessment, pre-service teachers were expected to identify climate risk as a systemic problem and develop alternative solutions and teaching strategies. As a final project, the pre-service teachers were also expected to prepare a lesson plan integrating climate change and system dynamics tools.

Table 3.2. Outline of the climate change education course.

Class Topics	Week
Introduction and Course Expectations Systems Thinking Practices	Week 1
Understanding Earth as A System	Week 2
Land Systems	Week 3

Table 3.2 Outline of the climate change education course. (cont.)

Class Topics	Week
Population Dynamics	Week 4
Consumption	Week 5
Wealth and Emissions	Week 6
Greenhouse Effect and Air Systems	Week 7
Water Systems	Week 8
Spring Break	Week 9
Lake Urmia Task	Week 10
Interconnected Systems	Week 11
Strategies For Teaching Climate Change To K-12 Students	Week 12
C-ROADS and EN-ROADS Climate Solutions Simulator	Week 13
Managing Controversy and Misconceptions	Week 14

3.3. Data Collection Tools

3.3.1. Demographic Form

A demographic form was used to collect information about the participants (Appendix A). This form included the participants' gender, major, age, and whether they had taken a course on environmental education and systems thinking.

3.3.2. Lake Urmia Vignette

The original version of The Lake Urmia Vignette (LUV) (Appendix B) was developed by Davis *et al.* (2020). This tool aims to assess students' understanding of the complexity of a socio-environmental problem, in other words, to assess their systems thinking skills. Systems thinking skills are measured in terms of students' ability to recognize interconnections and feedback loops when evaluating the outcomes of an

environmental system (Davis *et al.*, 2020). There is a real-life case about a socio-environmental problem from Lake Urmia in Iran that reveals how the impact of many social, political, economic, organizational, and environmental factors can lead to an environmental disaster. There are two open-ended questions to identify the problem within relations and propose solutions to this problem. Davis and colleagues (2020) calculated inter-coder reliability between two different coders in two rounds of 0.84 and 0.96, which were considered highly correlated.

David and colleagues (2020) added some questions to ensure the validity of the Lake Urmia vignette. One was an additional feedback loop question to compare with the vignette. This question was included to test the students' familiarity with feedback loops. According to the results, knowledge of feedback loops was positively correlated with LUV scores ($p < 0.05$). Also, it was noted that students who scored high on the feedback loop question made more interactions between variables in the Lake Urmia vignette. Therefore, it was considered appropriate for assessing the understanding of feedback loops and causal relationships.

In the current study, Lake Urmia Vignette was used as a data collection tool and the same questions were asked again with different answering methods (explaining and drawing causal loops). Thus, the pre-service teachers answered a total of four questions as a group. It was aimed to investigate the understanding of complexity by drawing causal loop diagrams because causal loop diagrams help to visualize the structure and behavior of systems. Table 3.2 presents the original questions. It should be noted that the content of the questions was not revised. Only the method of answering the questions was enhanced. As in the original version, the pre-service teachers provided written explanations. In addition to that, they answered the same questions using causal loop diagrams. The adaptation made in this study was to ensure that the pre-service teachers answered the same questions using causal loop diagrams.

Table 3.3. Descriptives statistics of participants.

Questions
Q1. What do you think ‘went wrong’ in Lake Urmia? Based on the provided text, and your own thoughts, write an explanation on why Urmia is suffering from its problems.
Q2. What do you think ‘went wrong’ in Lake Urmia? Based on the provided text, and your own thoughts please create or show causal loops. *
Q3. Given the problem, what should be done to protect the environment and ecosystem of Lake Urmia? Please write an explanation.
Q4. Given the problem, what should be done to protect the environment and ecosystem of Lake Urmia? Please create or show causal loops. *
*Note. In the original Lake Urmia vignette, questions were answered by written statements only. In the present study, causal loops were drawn in addition to written statements.

3.4. Procedure

During the literature review, many different methods of measuring systems thinking were explored. Scenarios were found to be an appropriate way to measure systems thinking, and thus it was decided to use the Urmia Lake Vignette tool, a real-life scenario, to measure pre-service teachers’ understanding of systems complexity. The questions in the original version of this tool were not changed; the same questions were asked to be answered in two different ways. The pre-service teachers completed the adapted Lake Urmia vignette with four questions, both in explanation and through the causal loop diagram as a group.

Before the data collection, the necessary permissions for the study were obtained from the Ethics Committee of Boğaziçi University (Appendix C), and the participants were informed with a consent form (Appendix D). The data was collected in the spring semester of the 2024 Climate Change Education course. The data was collected towards the end of the semester to familiarize students with causal loop diagrams. The data collection process lasted two class hours, during which the researcher observed how the

participants worked. The pre-service teachers answered each question as a group. The Lake Urmia vignette was provided as a Word document, and the data was collected digitally. Groups worked on their digital devices, such as tablets, laptops, etc. They were also provided with paper and pens if they needed them.

3.4.1. Data Analysis

This section details how the data analysis was carried out to answer the research questions (Appendix E).

3.4.2. Statistical Analysis

SPSS statistical software was used to analyze descriptive statistics such as mean, normality, minimum, maximum, frequencies etc., for each research question.

3.4.3. Examining Pre-service Teachers' Mental Models

The complexity of the mental models formed as a result of this study was examined in certain measures. The first research question examined the complexity of the mental models obtained due to the effort to transform the pre-service teachers' written statements into causal loop diagrams. In the second research question, the pre-service teachers were actively involved in the modeling process. They were allowed to create causal loop diagrams, thus visualizing the representation of mental models as causal loop diagrams. The third research question compares the complexity of two mental model representations obtained by two methods.

Richmond (2000) emphasized operational thinking, which expresses the importance of focusing on the structure of the system rather than focusing only on the elements of the system. At this point, in order to examine the structure of the system, firstly the link density was analyzed. However, link density may not be sufficient in some cases because models may have a linear or branched structure. This measurement

ignores the branched structure. Therefore, the Web-like Causality Index (WCI) proposed by Plate (2006) aims to measure the extent to which the models have a branched structure. A high WCI score is a measure of how far the model is from linear thinking (Plate, 2006).

Another important criterion for understanding dynamic systems is the inclusion of feedback loops. Therefore, a measure of feedback density was calculated to understand how the elements of the system are interconnected in terms of feedback loops (Naugle *et al.*, 2023).

Causal complexity was introduced by Naugle *et al.* (2023) as another important measure for examining the causal structure of models. This was based on the cyclomatic complexity originally introduced by McCabe (1976), and causal complexity was found to provide a more holistic perspective on the system complexity of models in terms of feedback loops (Naugle *et al.*, 2023).

Table 3.4. Measures for analyzing of mental models.

Measure	Criteria	Calculation
Link Density	Interconnection	Links (Edges)/nodes
Weblike Causality	Complexity	Branching nodes/total nodes
Feedback Density (D)	Feedback	$(E_{loop} + N_{loop}) / (E_{total} + N_{total})$ E: Edges (links)
Cyclomatic Complexity (M)	Complexity	Links – Nodes + 2 * Connected Components
Causal Complexity	Complexity	$M * (1 + D)$ = Cyclomatic Complexity * (1 + Feedback Density)

Figure 3.1 showed the relation between all measures. Link density is a measure of the ratio of links to nodes. Web-like causality index is a measure of how much branching structure there is. Feedback density relates to the extent to which feedback loops are incorporated into the whole structure. Causal complexity was especially

related to both cyclomatic complexity and feedback density. The presence of feedback loops affects the causal complexity of the models by increasing the feedback density.

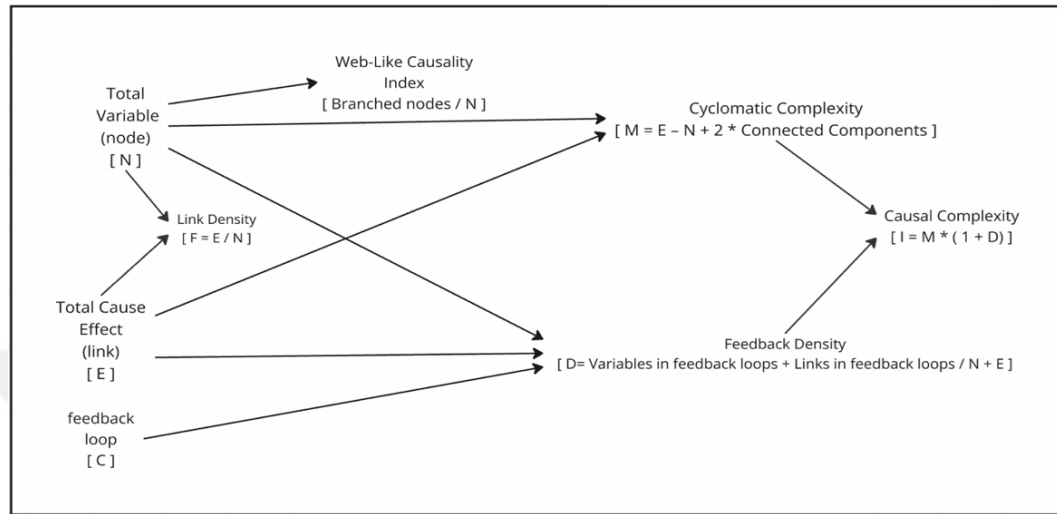


Figure 3.1. Relations between measures.

3.4.3.1. Data Analysis for the First Research Question. RQ 1.: What are the pre-service teachers' mental models on climate change-based case scenarios? To answer the first research question, the written responses to questions 1 and 3 in the Lake Urmia vignette were analyzed using an example from the study by Haque *et al.* (Appendix F). It follows the method of transforming qualitative data into causal loop diagrams constructed by Kim and Andersen (2012). In the first stage, words in the textual responses were color-coded. Terms representing variables were colored red, and terms indicating causal links were colored green. In the second stage, a word-arrow diagram showing the causal relationships for the coded terms was formed. A mental model (causal loop diagram) was obtained in the last stage according to a word-arrow relationship (Kim and Andersen, 2012). Thus, the researcher visualized pre-service teachers' textual answers to what is wrong with the lake and what might be done as a result. A tool which is useful for system dynamics, Vensim was used for visualization. Vensim is a software developed by Ventana Inc. that facilitates the development, exploration, prediction and analysis of simulation models. It can be utilized as a learning environment and is well suited for creating system models, such as causal loop diagrams and stock-flow diagrams (Eberlein and Peterson, 1992).

To reach consensus on the mental model representations throughout the phases of the analysis, twenty-six meetings were organized with an expert in systems thinking, each lasting approximately one hour. For the first research question, the researcher transformed all the written explanations into causal loop diagrams. The expert also converted the written explanations into causal loop diagrams and reviewed each of them to confirm their validity. Then the researcher and the expert held some meetings. During the meetings, the transformations were discussed, and a consensus was reached. Finally, the agreed causal loop diagrams were finalized by the researcher. The complexity of the representations of pre-service teachers' mental models was examined in terms of link density, web-like causality index, feedback density, cyclomatic complexity, and causal complexity.

3.4.3.2. Data Analysis for the Second Research Question. RQ 2.: What is the level of complexity of preservice teachers' causal loop diagrams on climate change-based case scenarios?

To answer the second research question, causal loop diagrams in the Lake Urmia Vignette in response to questions 2 and 4 were analyzed as shown in the example (Appendix G). A post-production phase was carried out to iterate and improve the quality of causal loop diagrams. In this study, the post-production process was followed in digitising the causal loop diagrams prepared by pre-service teachers. This stage was divided into two processes format and content editing. For format editing, some arrangements were proposed for variables (such as expressing the variable as a name, combining variable names repeated in more than one causal loop diagram) and causal links (such as polarity, defining feedback loops).

In addition, it was stated that it may revise the content of the causal loop diagrams in consultation with the literature and experts, while respecting the original structure constructed by participants (Lopes and Videira, 2015). In order to reach a consensus on the analysis with the an expert in system thinking, a collaborative working file was created and the drawings were digitized using Vensim software. This is

important for the analysis to proceed smoothly. Therefore, the causal loop diagrams were revised in this study by consulting the literature and expert consultancy.

First, the drawings of the pre-service teachers who responded to the questions about what was wrong with the lake and what could be done about it with causal loop diagrams were combined through the common variables (nodes), if any, if they were drawn separately for each question. Since the questions in the Lake Urmia vignette were asked separately as 2 and 4, it is possible that they were drawn separately. Combining causal loop diagrams if it is possible, prevents double counting of the same variable. Lastly, all the causal loop diagrams drawn by the pre-service teachers were transferred to the Vensim software. The complexity of the transferred causal loop diagrams was calculated using measures such as link density, web-like causality, feedback density, cyclomatic complexity, and causal complexity.

Moreover, it was questioned how accurately the causal loop diagrams could be drawn regarding causality. Therefore, causal loop diagrams were reviewed by the researcher in terms of causality, and variables and links that did not have a causal relationship between them were colored gray without changing the structure of the causal loop diagram. Then, following the same steps, the complexity of revised causal loop diagrams was examined using link density, web-like causality, feedback density, cyclomatic complexity, and causal complexity measures.

3.4.3.3. Data Analysis for the Third Research Question. RQ 3.: To what extent do systems complexity of preservice teachers' written explanations and causal loop diagrams on climate change-based case scenarios differ?

Figure 3.2 provides understanding and comparing mental models exposed by writing and causal loop diagrams. During the data collection process, the pre-service teachers expressed their mental models through writing and causal loop diagrams. The representation of participants' mental models was created by the researcher based on the data provided through written responses. On the other hand, the pre-service

teachers reflected their mental models by drawing a causal loop diagram. As the pre-service teachers' ability to draw causal loop diagrams was an important factor, the causal loop diagrams were analyzed in terms of the quality of causality. The researcher then created a representation of the participants' mental model based on the data provided by the causal loop diagrams. At this point, the third research question investigated whether there was a difference in the complexity of the representations of pre-service teachers' mental models based on written or causal loop diagrams.

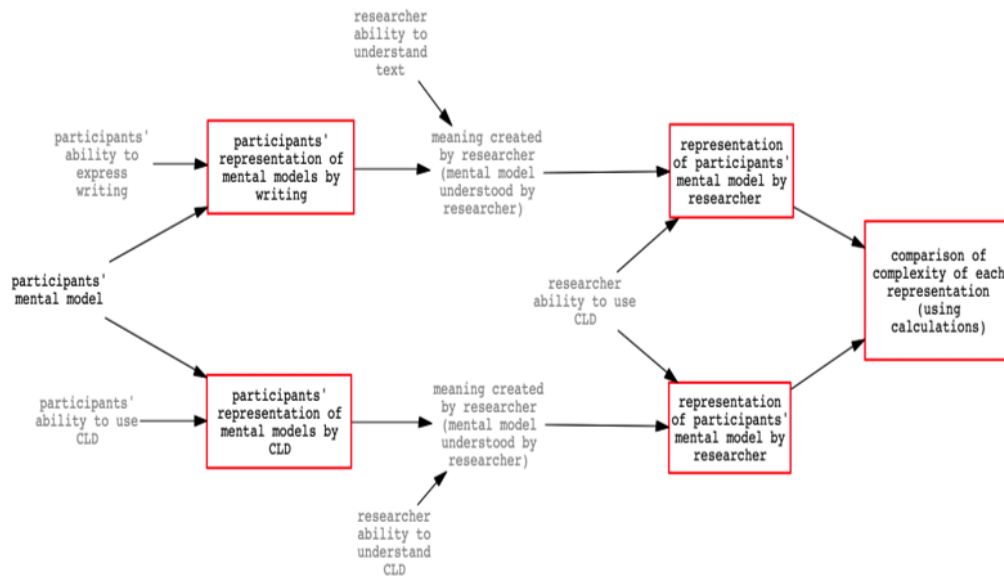


Figure 3.2. The process of understanding and comparing mental models.

To answer the third research question, the representations of the mental models obtained from the written responses and the representations of the mental models obtained from the causal loop diagrams were compared in terms of link density, web-like causality, feedback density, and cyclomatic complexity and causal complexity.

Firstly, whether there is a significant difference between the mental models obtained from written responses and mental models obtained from causal loop diagrams in terms of link density was examined. Since the data of mental models obtained from causal loop diagrams were not normally distributed, the Wilcoxon test was used, which is a non-parametric test.

Secondly, whether there is a significant difference between the mental models obtained from written responses and mental models obtained from causal loop diagrams in terms of the web-like causality index was examined. Since the group number was less than 30, (N=17) Wilcoxon test was used, which is a non-parametric test.

Thirdly, whether there is a significant difference between the mental models obtained from written responses and mental models obtained from causal loop diagrams in terms of feedback density was examined. Since the participant group number was less than 30, (N=17) Wilcoxon test was used, which is a non-parametric test.

Fourthly, whether there is a significant difference between the mental models obtained from written responses and mental models obtained from causal loop diagrams in terms of cyclomatic complexity was examined. Since the participant group number was less than 30 (N=17), a Wilcoxon test was used, which is a non-parametric test.

Lastly, whether there is a significant difference between the mental models obtained from written response and mental models obtained from causal loop diagrams in terms of causal complexity was examined. Since the participant group number was less than 30 (N=17), a Wilcoxon test was used, which is a non-parametric test.

4. RESULTS

4.1. Results of an Expert Causal Loop Diagram

The researcher and a systems thinking expert developed a causal loop diagram based on the Lake Urmia vignette to provide a basis for analyzing mental models. First, they identified the variables in the text and established the links between them according to their causal relationships. Figure 4.1 shows the causal loop diagram was modelled by using Vensim software. Nouns represent variables, and arrows represent relationships. (+) indicates same-direction relationships in red, and (-) indicates opposite-direction relationships in green. A total of 22 variables were identified, along with 31 cause-effect relationships. Furthermore, the model comprises 13 feedback loops. The link density value was found to be 1.41, the web-like causality index was found to be 0,545, the feedback density value was found to be 1.00, the cyclomatic complexity value was found to be 11.00, and the causal complexity value was found to be 22.00

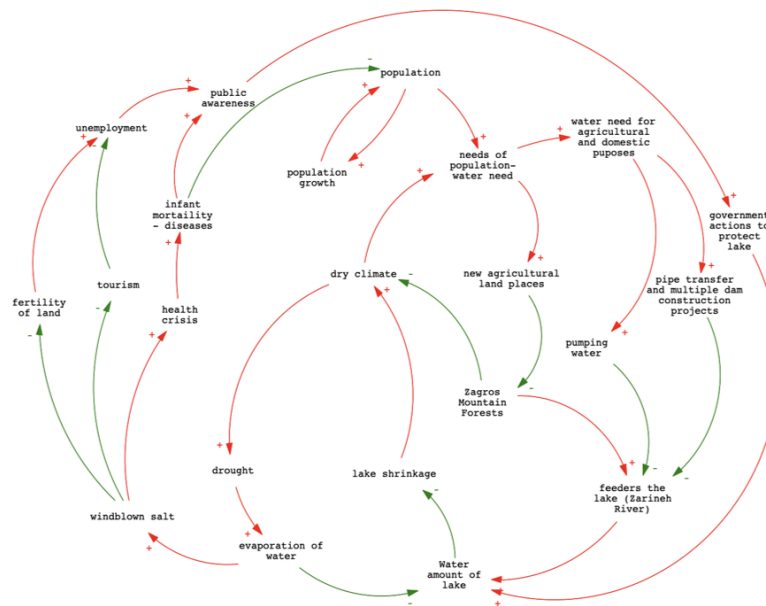


Figure 4.1. An expert causal loop diagram for Lake Urmia vignette.

4.2. Results of the First Research Question

A mental model was created by examining participants' written explanations to questions 1 and 3 in the Lake Urmia vignette. Thus, preservice teachers' mental models of defining a problem related to global climate change and proposing solutions to that problem were visualized by converting text into causal loop diagrams. To examine the structure of the mental model derived from written explanations, several analyses were performed. Table 4.1 presents the descriptive statistics for each group's mental models derived from written explanations. The results indicated that the mean number of variables was 15.94 ($n = 17$, $SD = 5.629$), with a minimum value of 7 and a maximum value of 24. The mean number of cause-and-effect relationships was 14.29 ($n = 17$, $SD = 5.241$), with a minimum value of 6 and a maximum value of 22.

Table 4.1. Descriptive statistics for written responses of groups (from text to CLDs).

Measures	<i>n</i>	<i>Mean</i>	<i>Std. Dev.</i>	<i>Min</i>	<i>Max</i>
Total Variable	17	15.94	5.629	7	24
Total Cause – Effect (link)	17	14.29	5.241	6	22
# of feedback loops	17	0.00	0.000	0	0

Table 4.2 shows the distribution of results of each group's written responses according to the number of variables, cause-effect (links), feedback loops, link density, web-like causality, feedback density, cyclomatic complexity, and causal complexity. The results of the possible model are also included in the table to provide a basis for evaluation.

Table 4.2. Results of each group's written responses according to measures.

Groups	Total Variable (Node)	Total Cause-Effect (Link)	# of Feed-back loops	Link Density	Web-Like Causality Index	Feed-back Density	Cyclo-matic Complexity	Causal Complexity
1	13	9	0	0.69	0.077	0.00	4.00	4.00

Table 4.2 Results of each group's written responses according to measures. (cont.)

Groups	Total Variable (Node)	Total Cause- Effect (Link)	# of Feed- back loops	Link Density	Web- Like Cau- sality Index	Feed- back Density	Cyclo- matic Com- plexity	Causal Com- plexity
2	19	19	0	1.00	0.316	0.00	4.00	4.00
3	19	21	0	1.11	0.263	0.00	4.00	4.00
4	13	11	0	0.85	0.077	0.00	2.00	2.00
5	24	19	0	0.79	0.167	0.00	3.00	3.00
6	24	18	0	0.75	0.125	0.00	4.00	4.00
7	12	13	0	1.08	0.583	0.00	3.00	3.00
8	8	9	0	1.13	0.375	0.00	3.00	3.00
9	9	8	0	0.89	0.222	0.00	3.00	3.00
10	17	17	0	1.00	0.294	0.00	2.00	2.00
11	20	18	0	0.90	0.2	0.00	2.00	2.00
12	10	8	0	0.80	0.1	0.00	2.00	2.00
13	22	20	0	0.91	0.273	0.00	6.00	6.00
14	14	13	0	0.93	0.214	0.00	3.00	3.00
15	22	22	0	1.00	0.227	0.00	4.00	4.00
16	18	12	0	0.67	0.111	0.00	4.00	4.00
17	7	6	0	0.86	0.286	0.00	1.00	1.00
Expert CLD	22	31	13	1.41	0.545	1.00	11.00	22.00

The mental model representations of each group based on the written responses, including measures, were also presented in Figure 4.2-Figure 4.18. First of all, in transforming the written responses into causal loop diagrams, the expressions in the text that could be considered variables were colored red.

The words that expressed causality were colored green. Then the word-arrow relationship was expressed linearly on the diagram. Causal loop diagrams were drawn based on the word arrow. The polarity of the links is determined and shown in different

colors, with red arrows representing same-direction causality between nodes and green arrows representing reverse causality.

For example, a data segment from the written answer of Group 1, which is given *Increased population has caused to forest's being transferred to agriculture to meet feeding resources*. According to the data segment, population, feeding resources, agriculture, forest was defined as variables in the diagram. It states that as the population increases, the use of forests for agriculture will increase, and the reason for this is to meet the need for food. There is a negative relationship between agriculture and forests. Forests will decrease as agriculture increases due to the need for food.

In other words, the relationship can be expressed as follows: as the population increases, the need for food increases, which increases agriculture, which decreases forests. When proceeding sequentially, it is necessary to consider that respondents may mention the same variable in the following sentence or another paragraph. Therefore, it is important to look at the data as a whole.

As seen in Figure 4.2-Figure 4.18, the structure of the mental models derived from the written explanations mostly had branched and linear causality, and no feedback loops were found among the groups. The detailed results for each measure were explained under the sub-headings of interconnection, feedback, and complexity. In Figure 4.2-Figure 4.18, in the written explanations column, words representing effect were colored green, and words representing cause were colored red.

Also in the mental model representation column, negative (opposite direction) causality was represented by green arrows, and positive (same direction) causality was represented by red arrows.

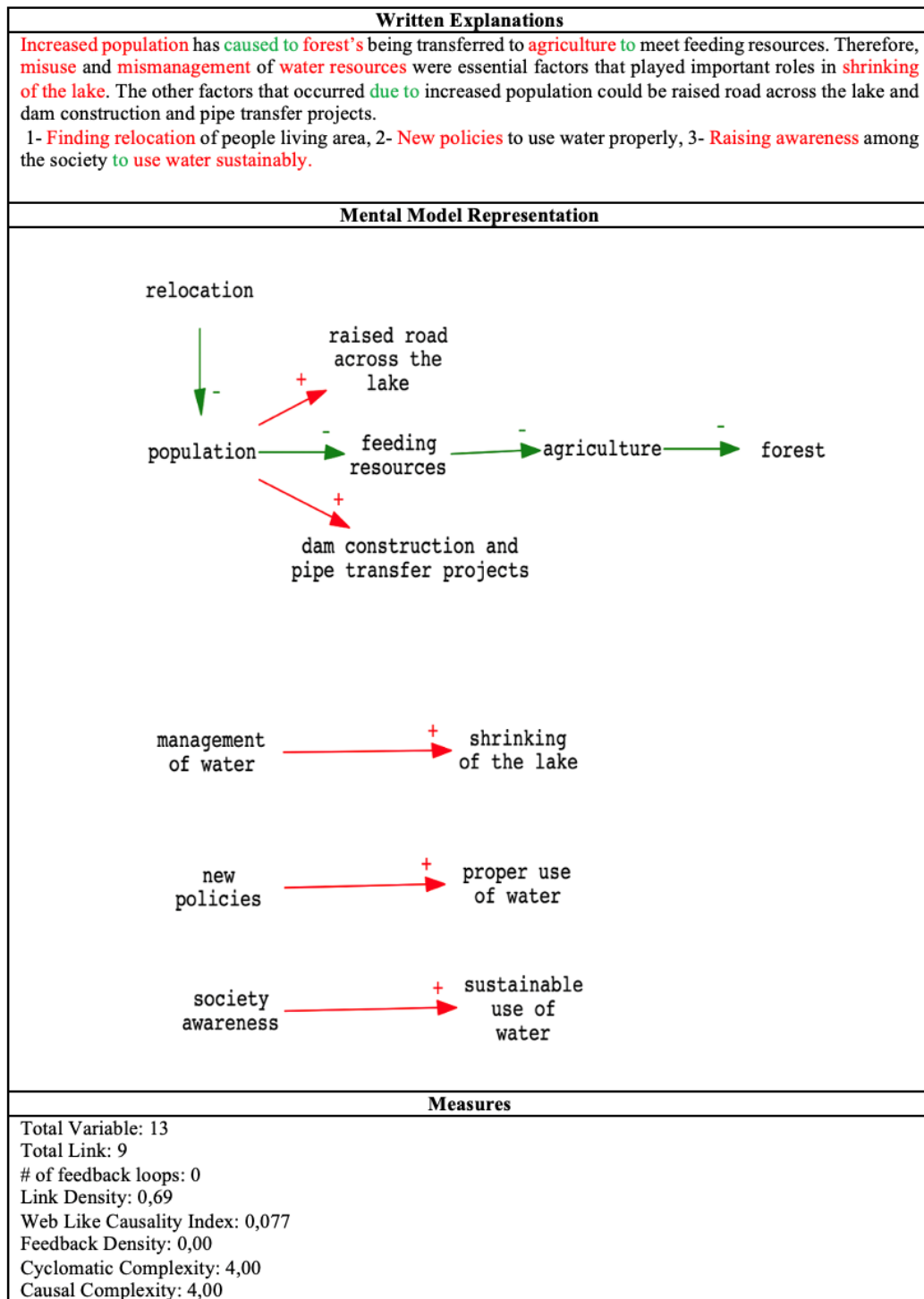


Figure 4.2. Mental models derived from written explanations for group 1.

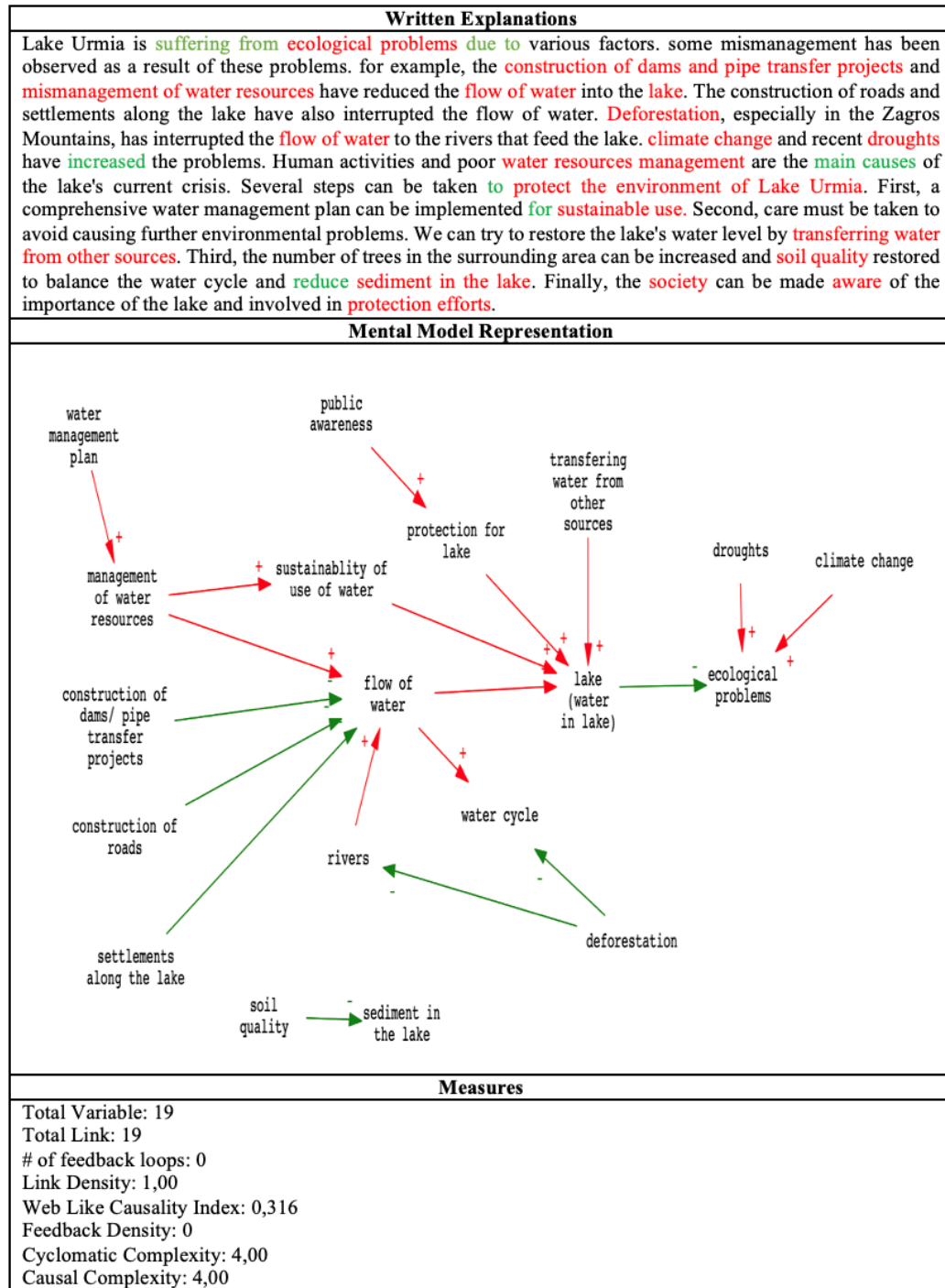


Figure 4.3. Mental models derived from written explanations for group 2.

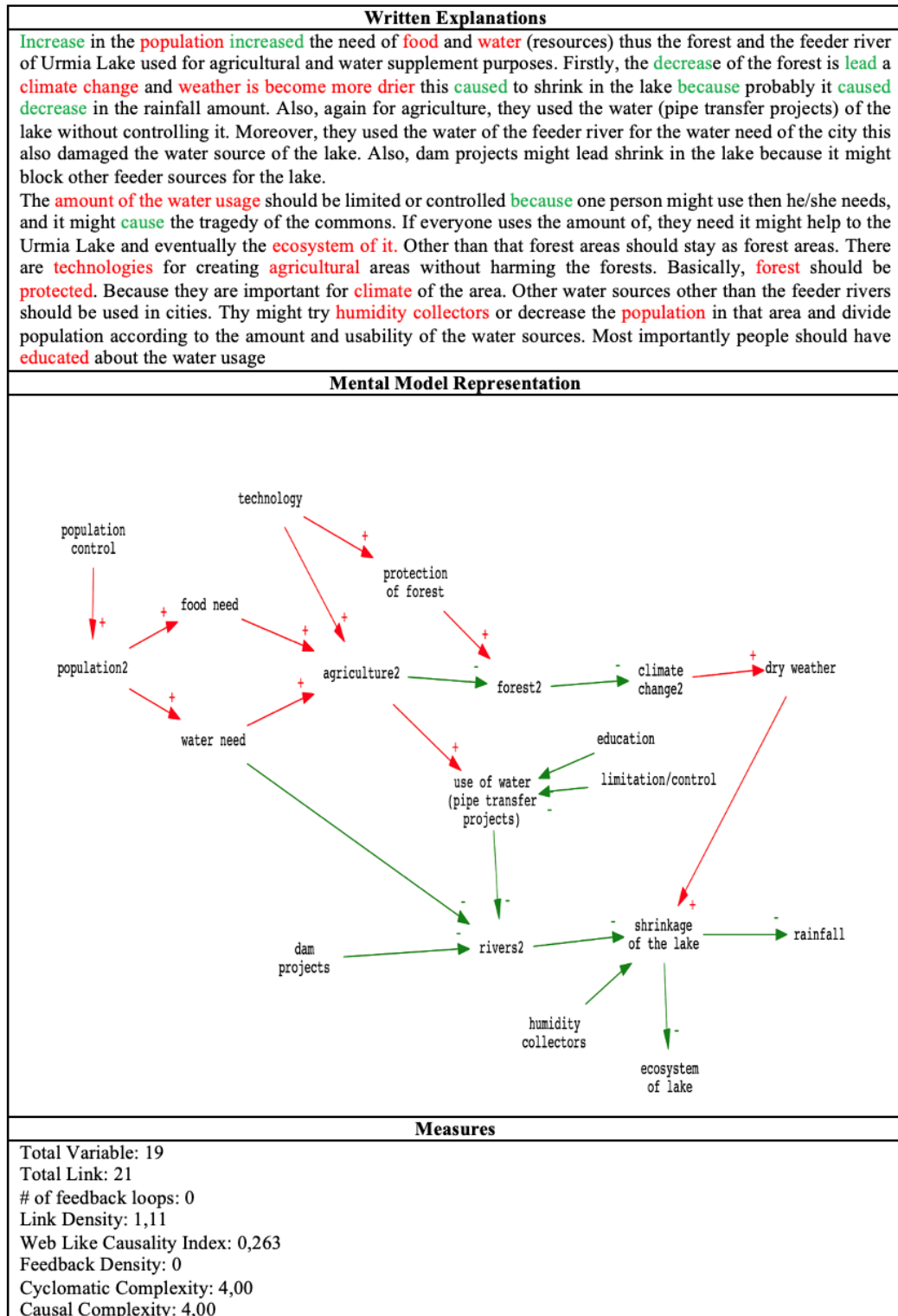


Figure 4.4. Mental models derived from written explanations for group 3.

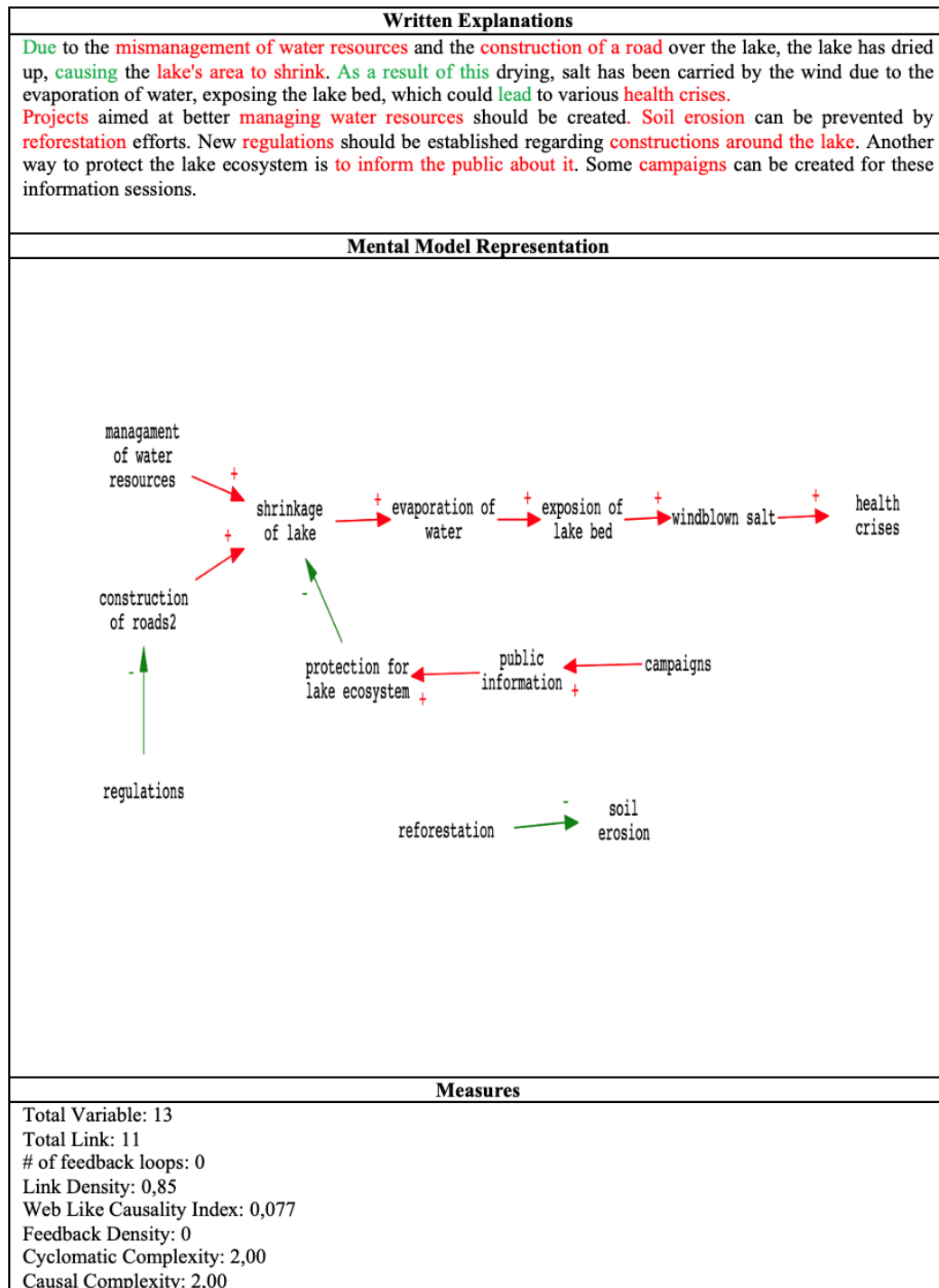


Figure 4.5. Mental models derived from written explanations for group 4.

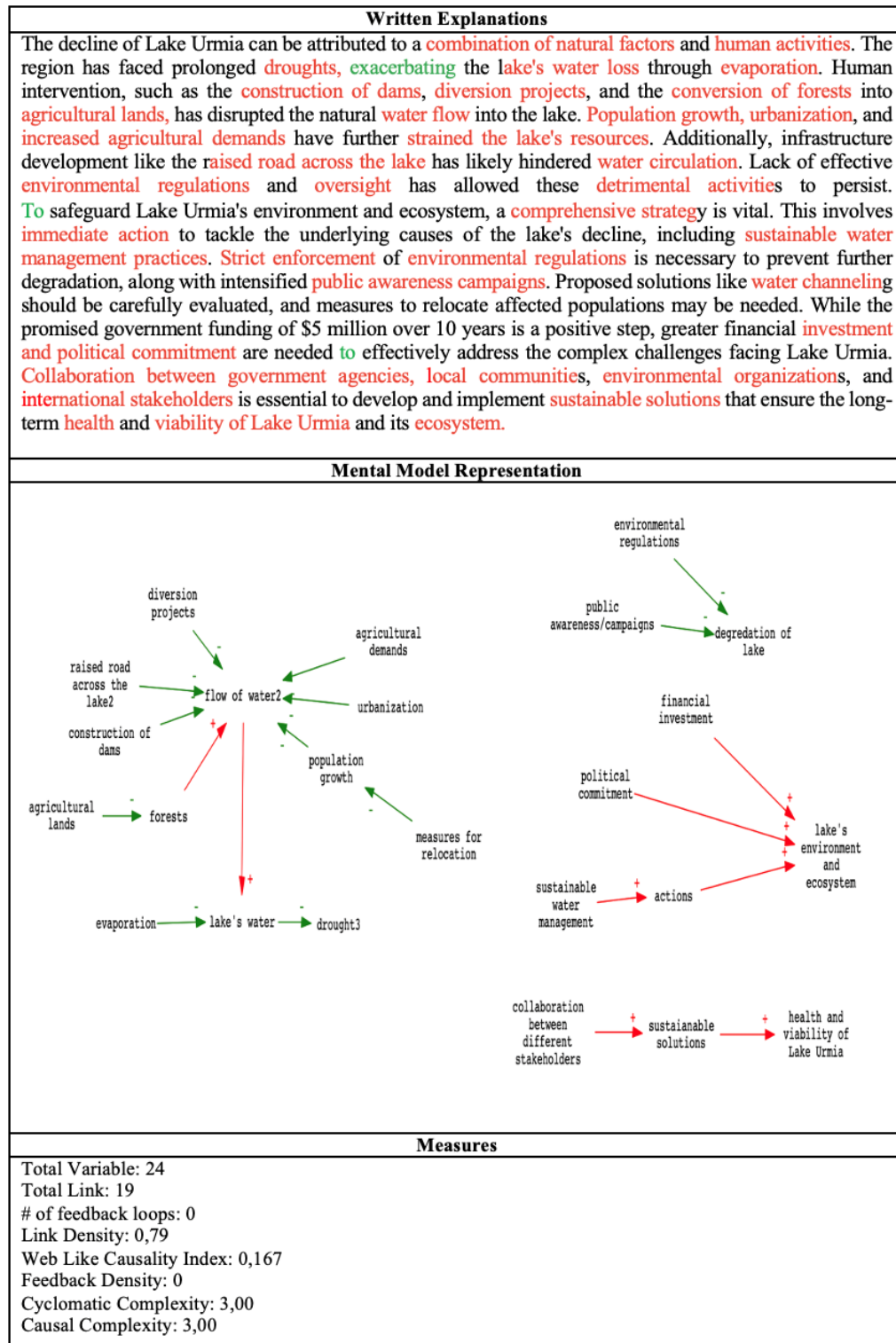


Figure 4.6. Mental models derived from written explanations for group 5.

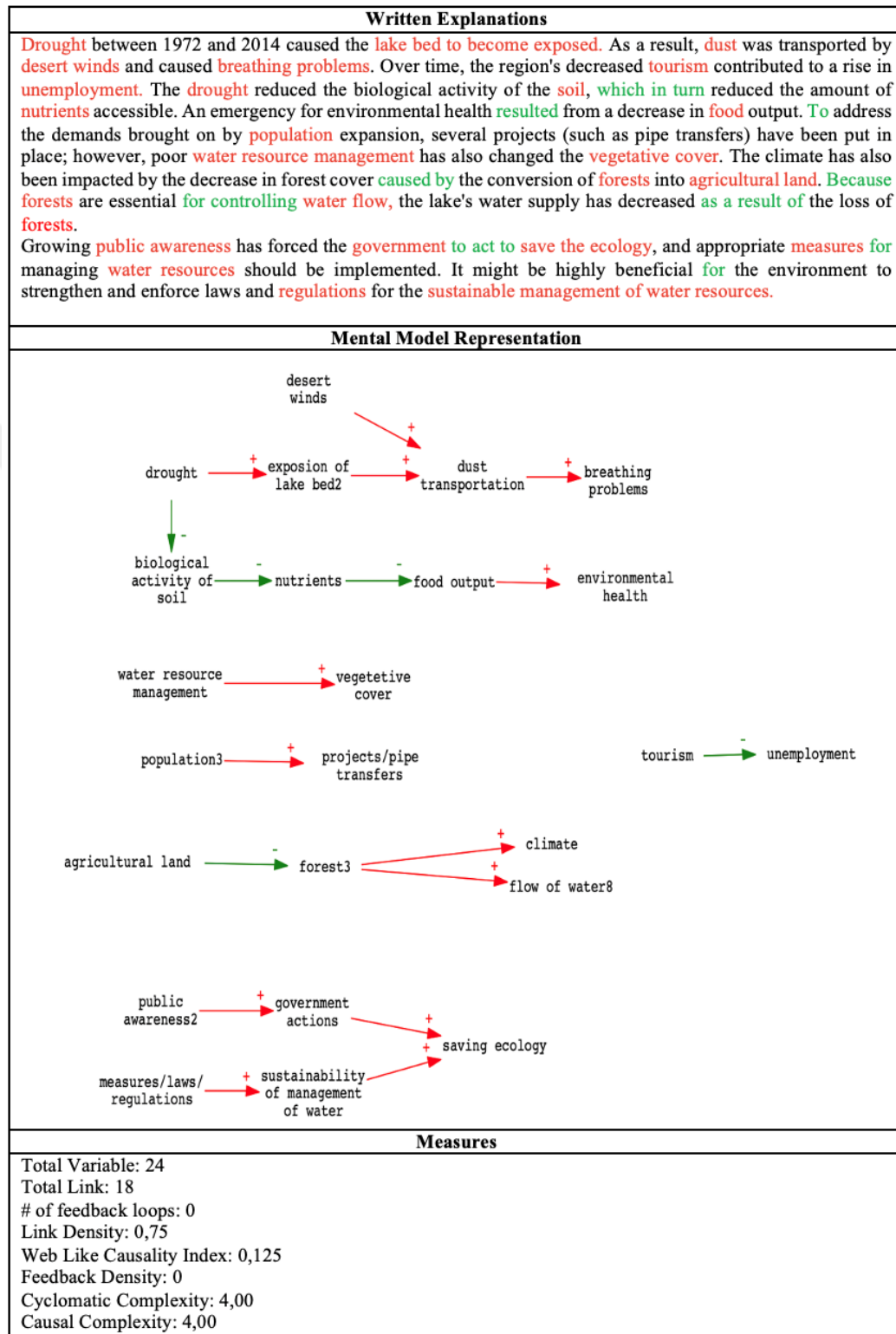


Figure 4.7. Mental models derived from written explanations for group 6.

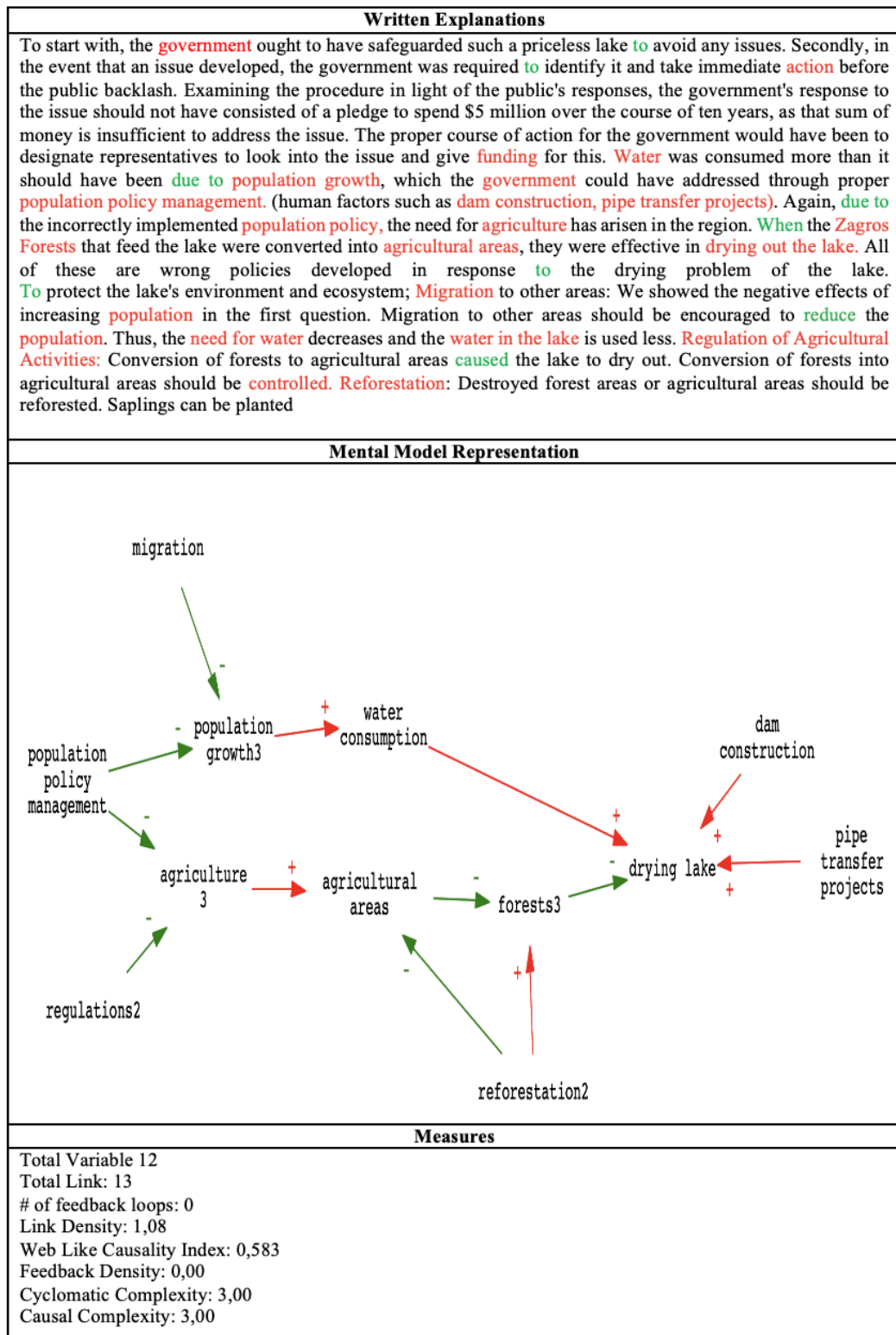


Figure 4.8. Mental models derived from written explanations for group 7.

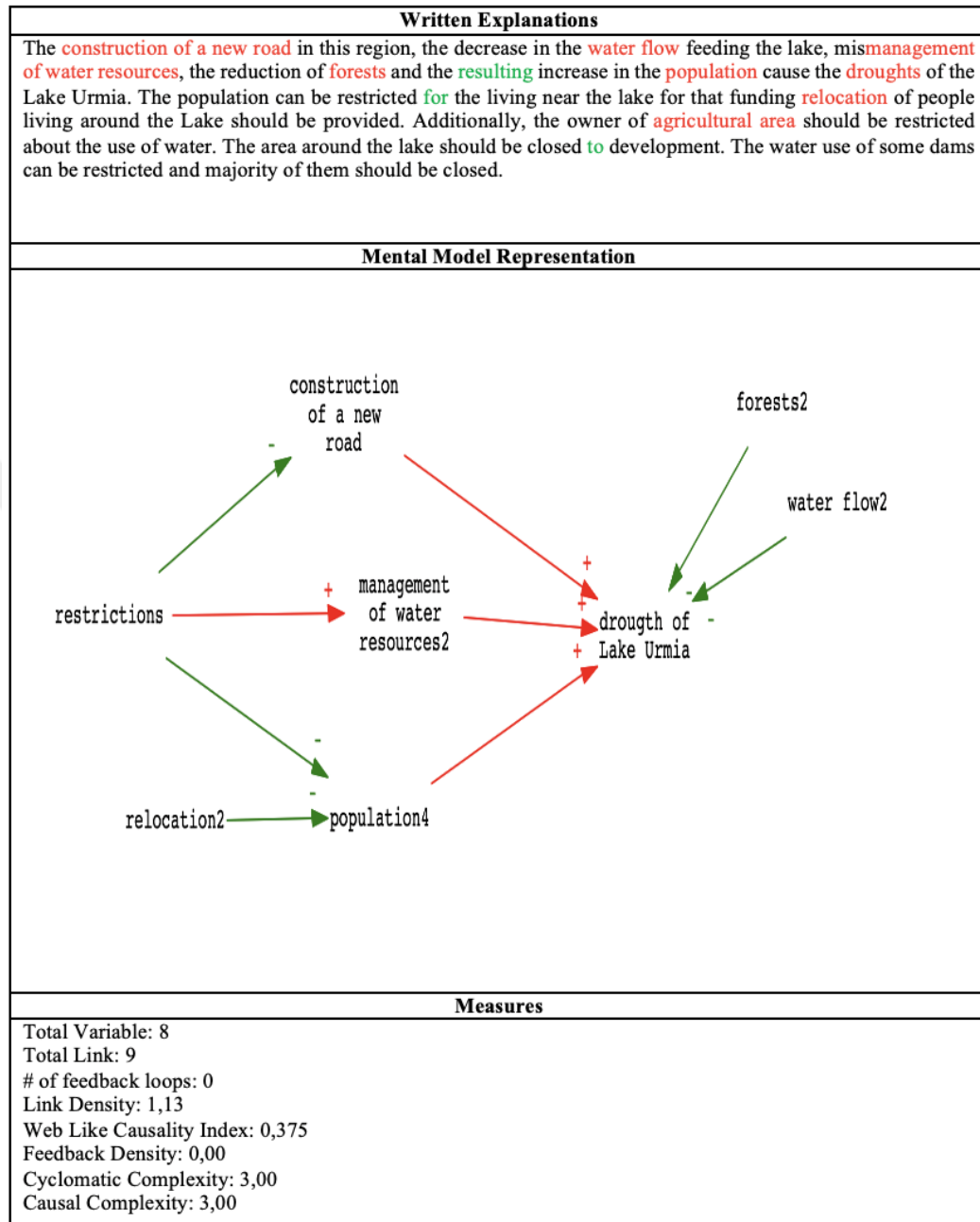


Figure 4.9. Mental models derived from written explanations for group 8.

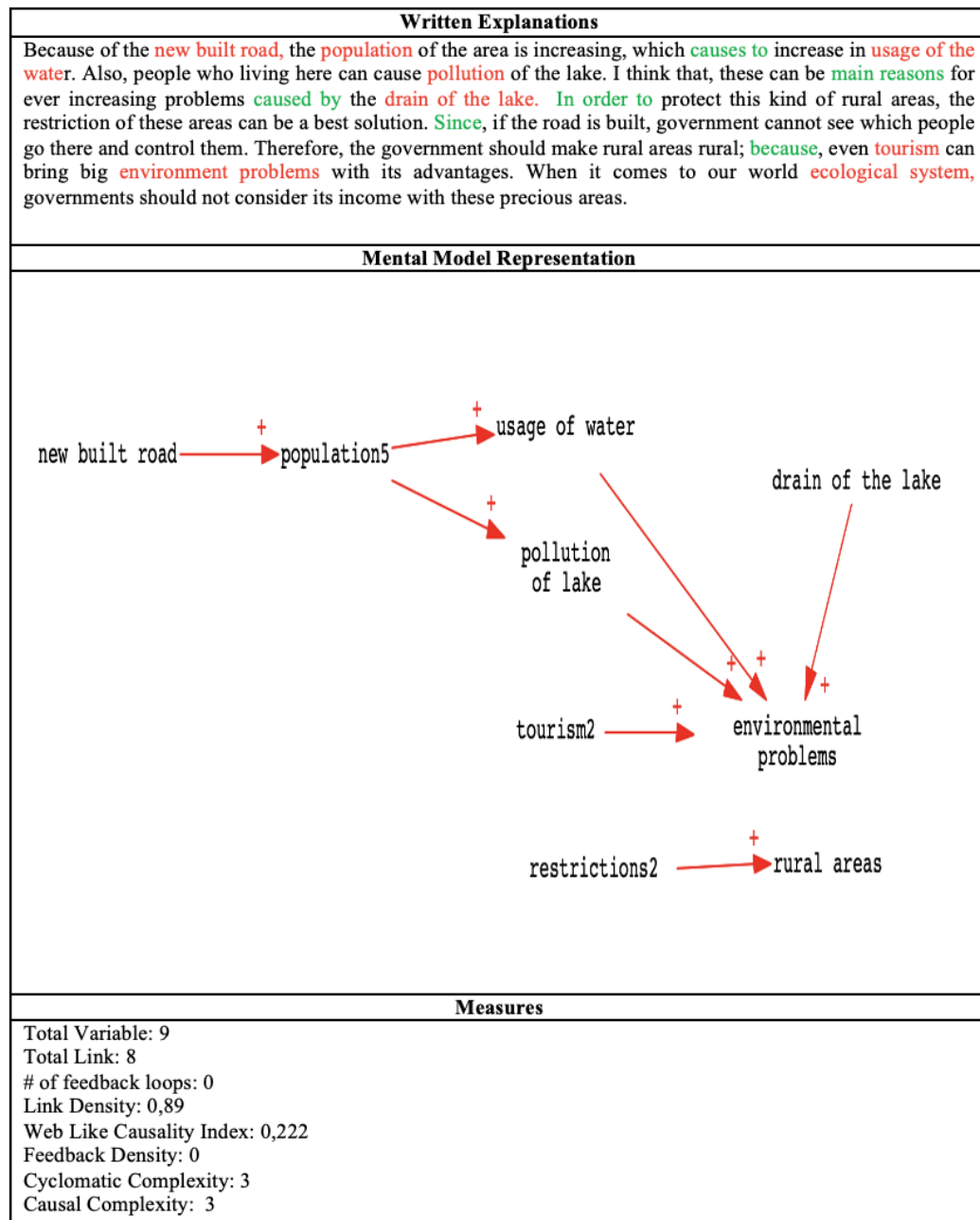


Figure 4.10. Mental models derived from written explanations for group 9.

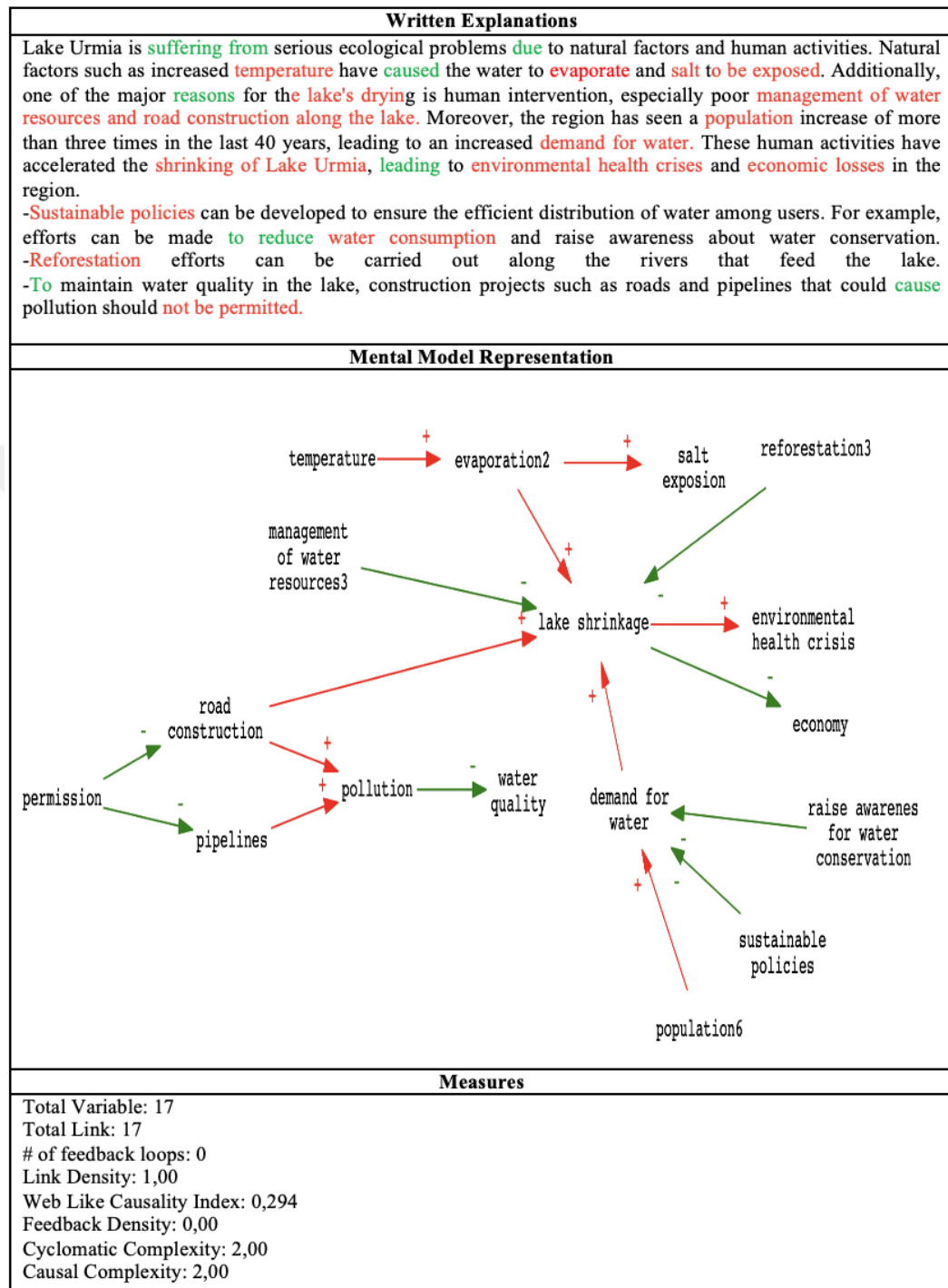


Figure 4.11. Mental models derived from written explanations for group 10.

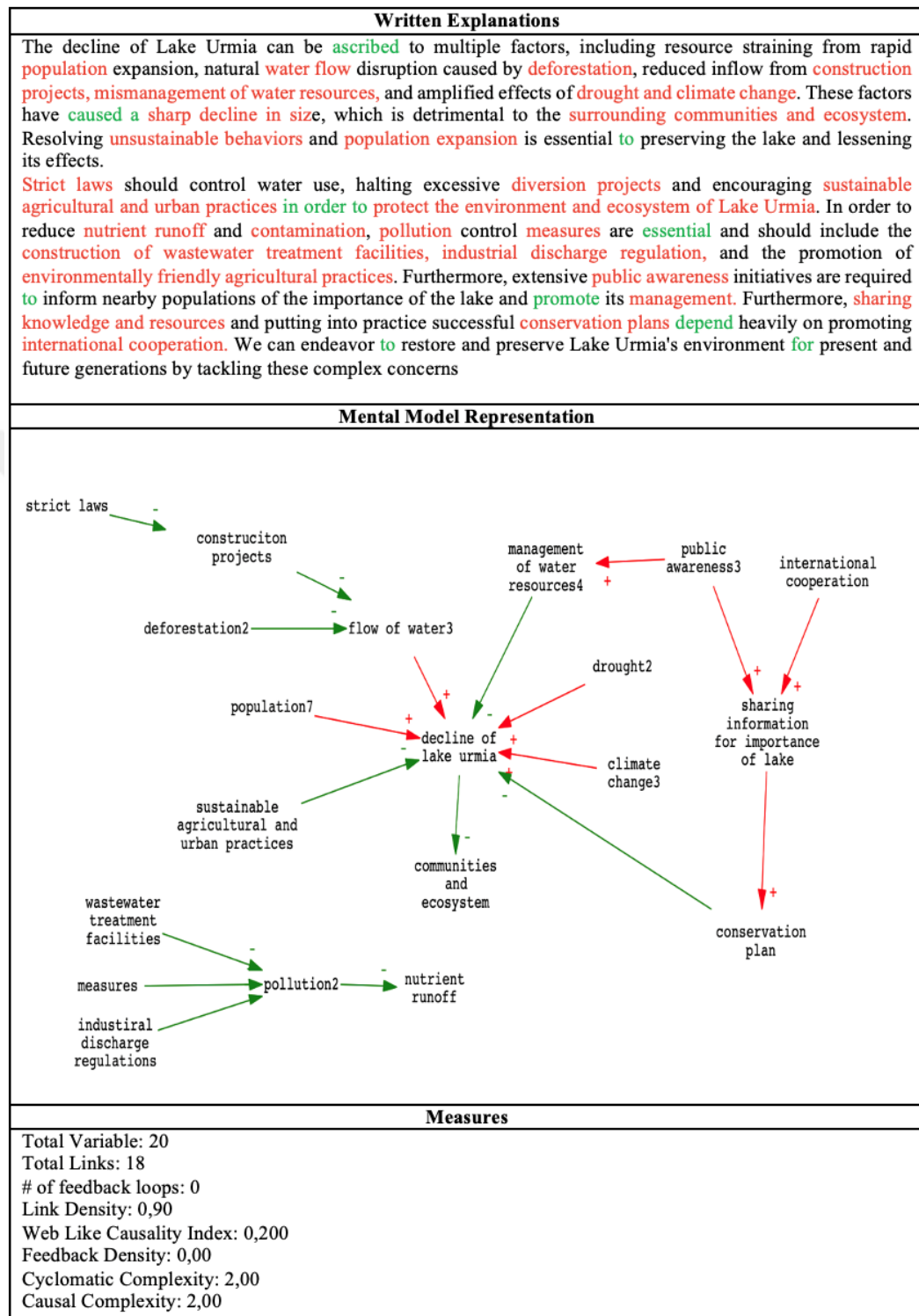


Figure 4.12. Mental models derived from written explanations for group 11.

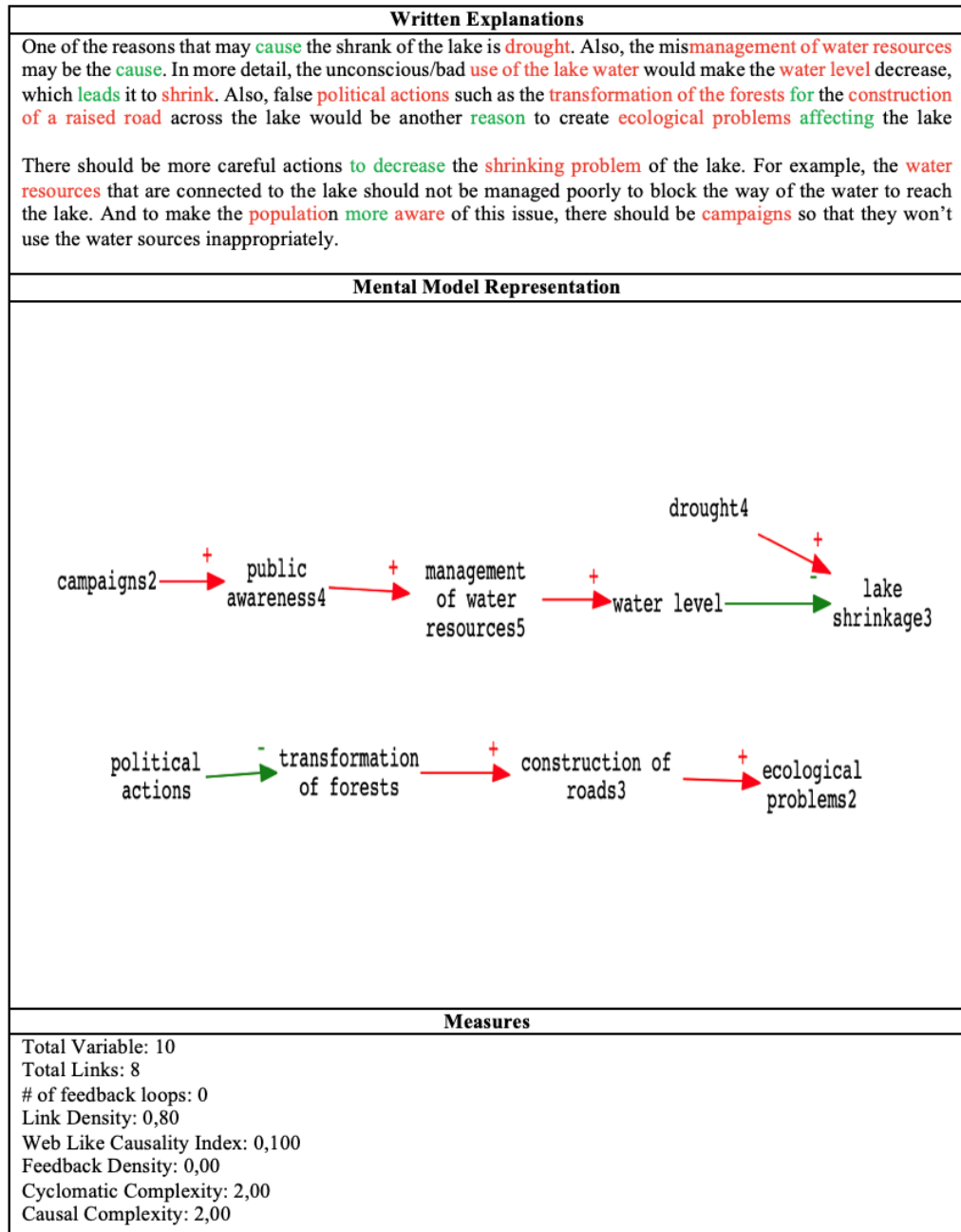


Figure 4.13. Mental models derived from written explanations for group 12.

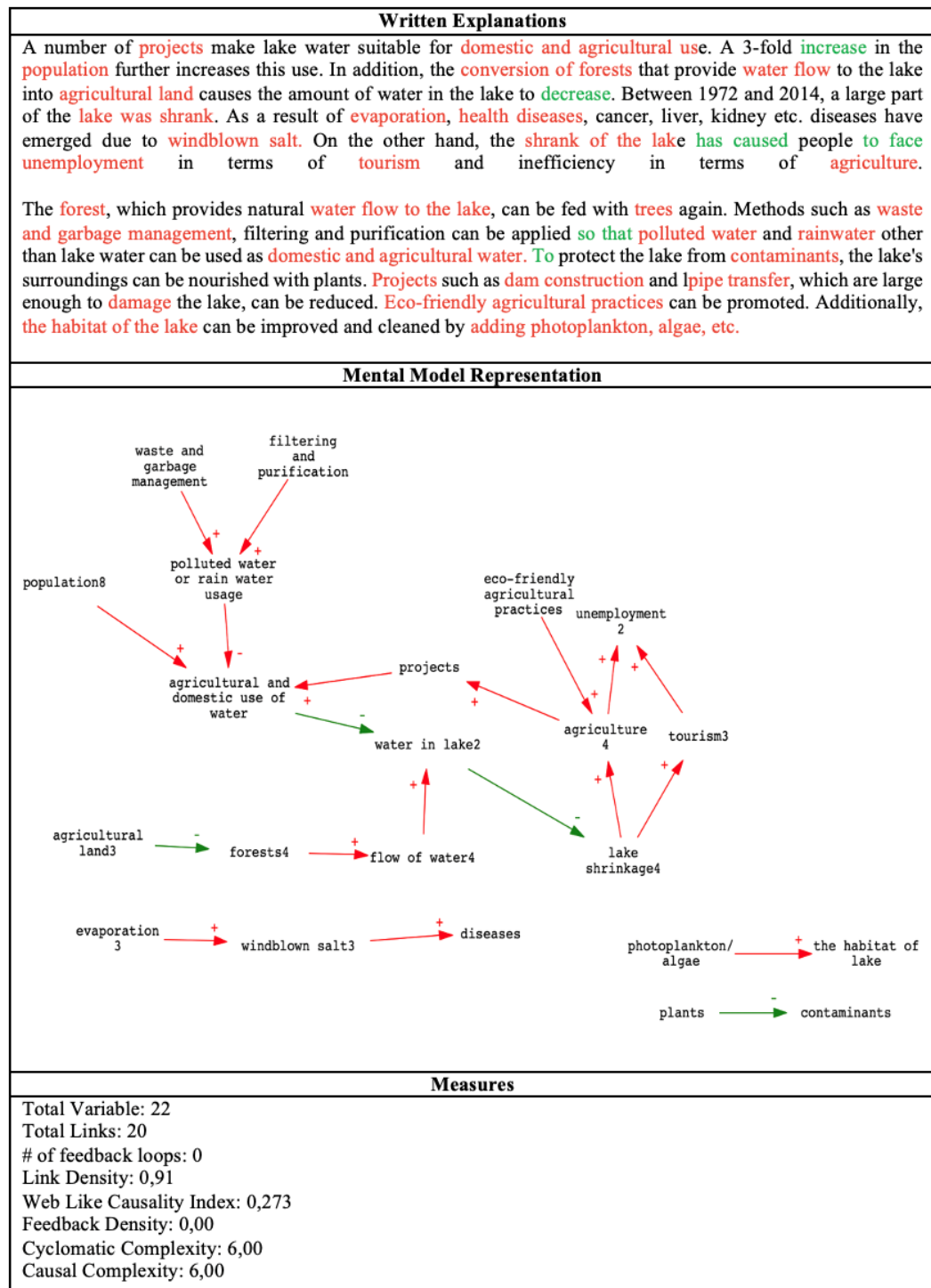


Figure 4.14. Mental models derived from written explanations for group 13.

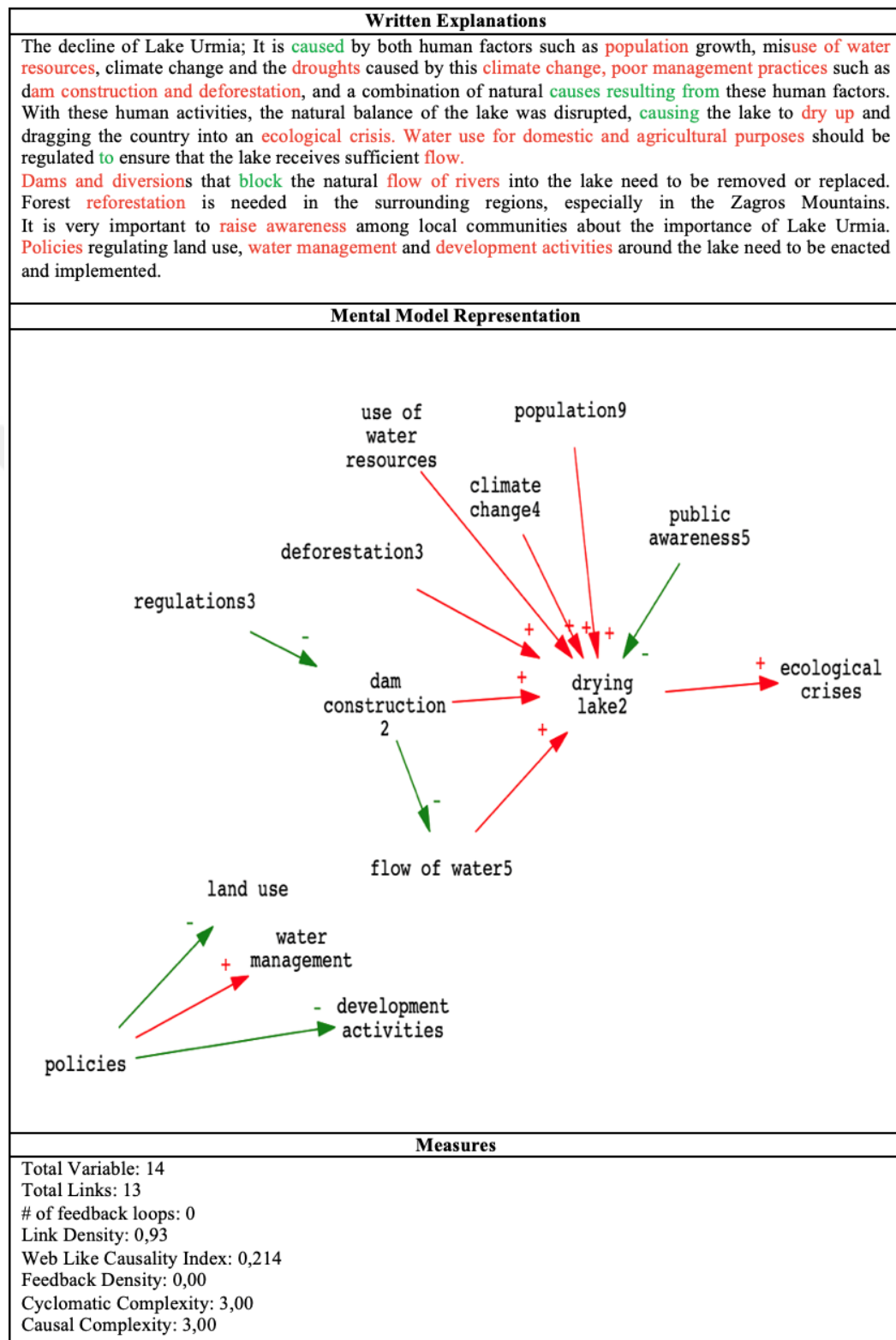


Figure 4.15. Mental models derived from written explanations for group 14.

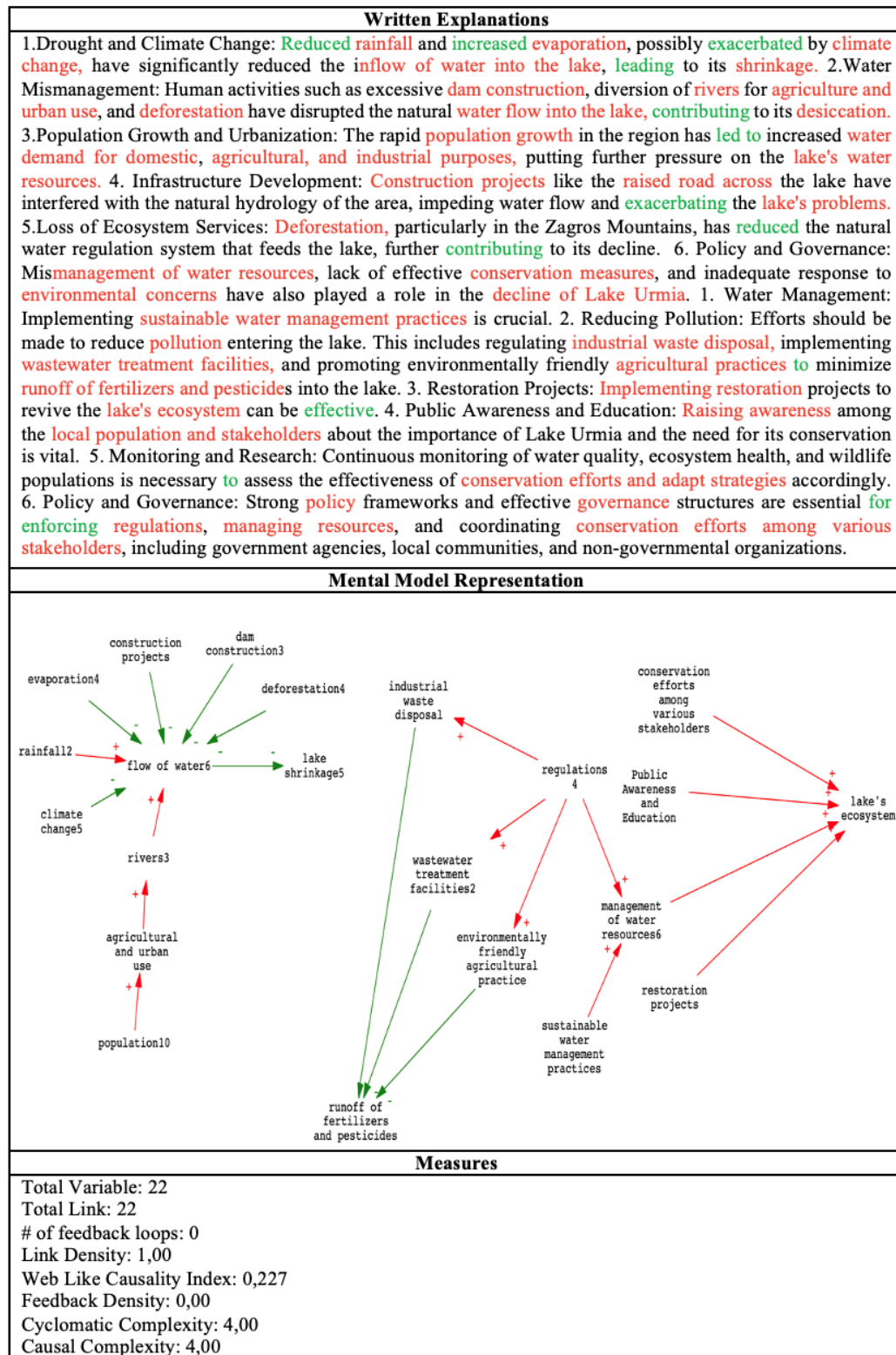


Figure 4.16. Mental models derived from written explanations for group 15.

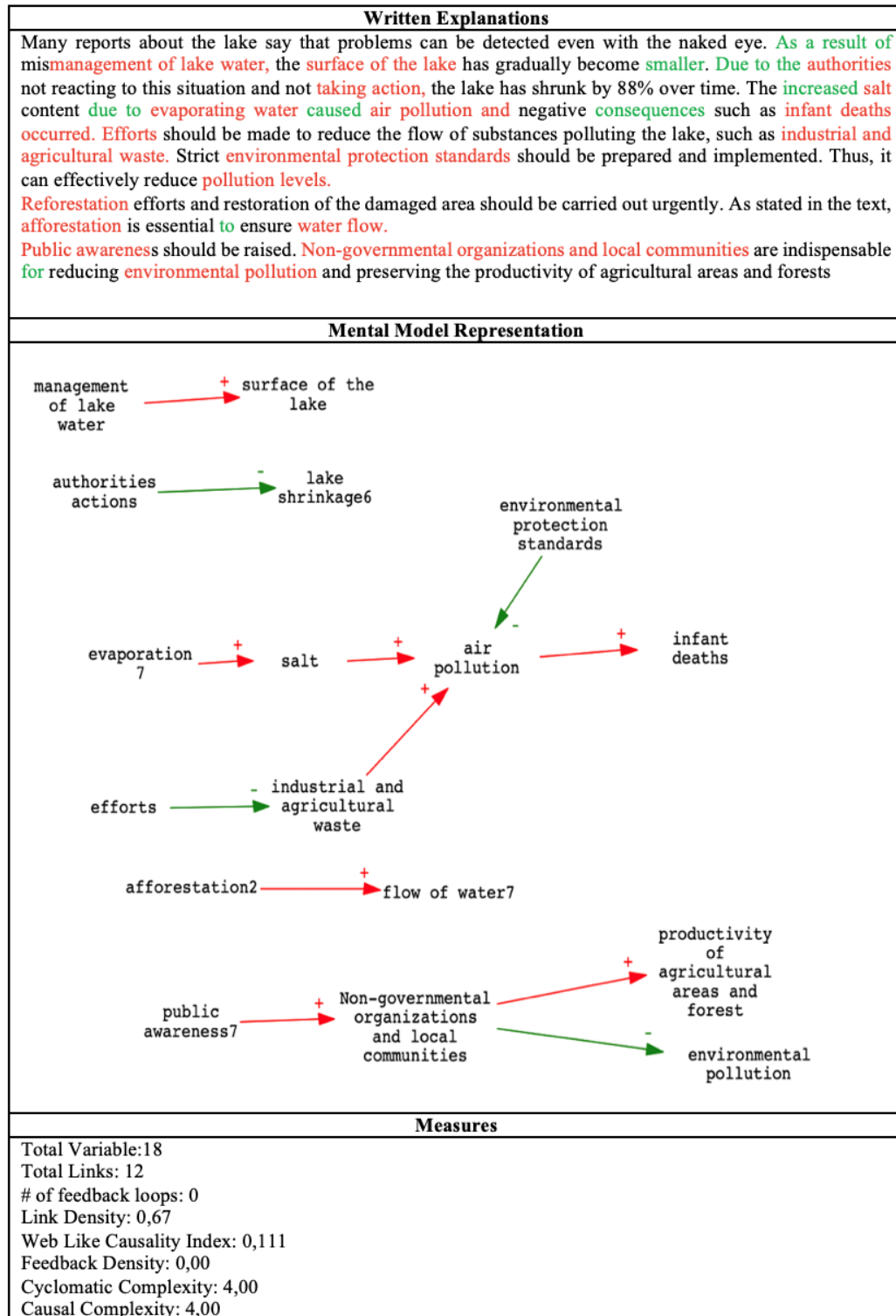


Figure 4.17. Mental models derived from written explanations for group 16.

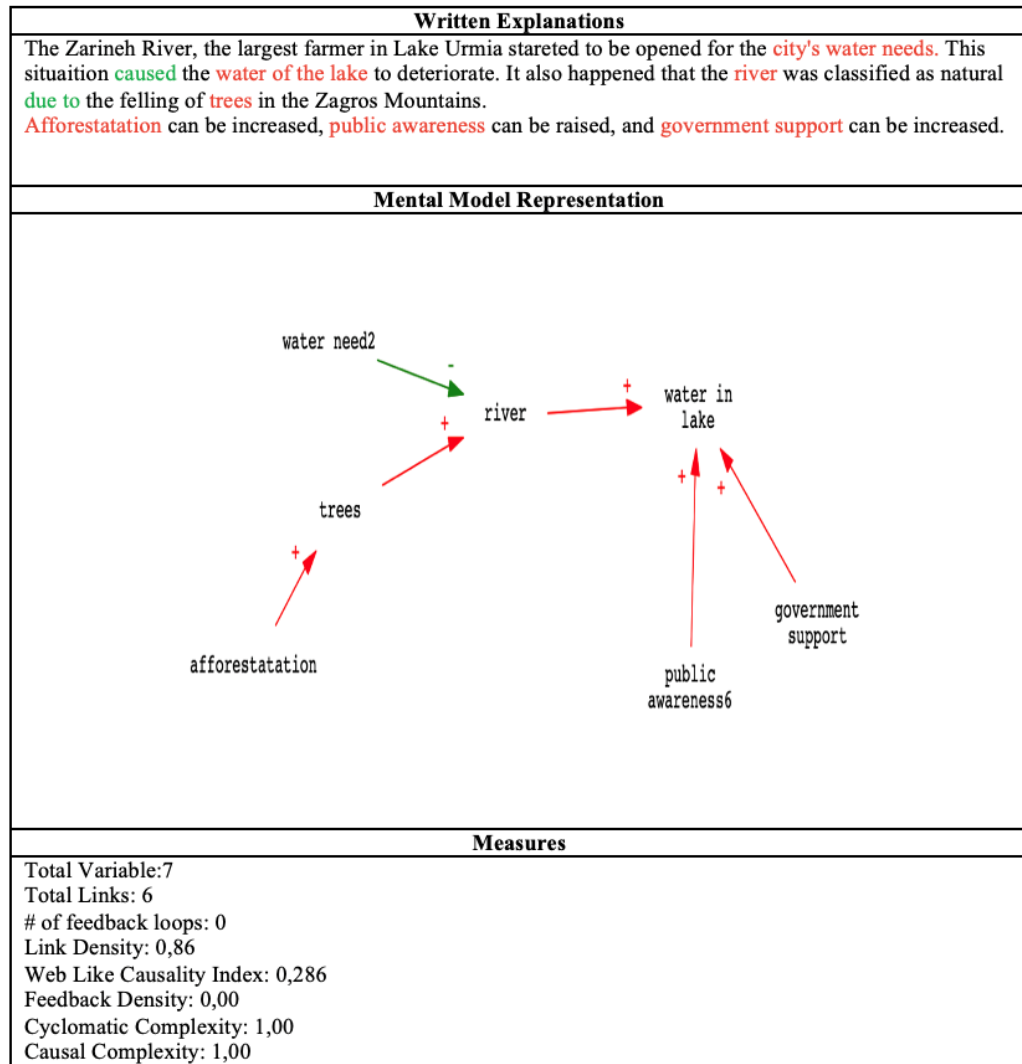


Figure 4.18. Mental models derived from written explanations for group 17.

4.2.1. Interconnections

Link density was calculated to measure the interconnectedness of the mental models. It is the ratio of the number of links to the number of nodes. A value greater than 1 means that the number of links is greater than the number of variables (nodes), while a value less than 1 means that the number of variables (nodes) is greater than the number of links.

Figure 4.19 shows that out of 17 groups, eleven have a link density less than 1, three have a link density equal to 1, and three have a link density greater than 1. This result shows that in the representations of most of the groups, the number of variables is greater than the number of links.

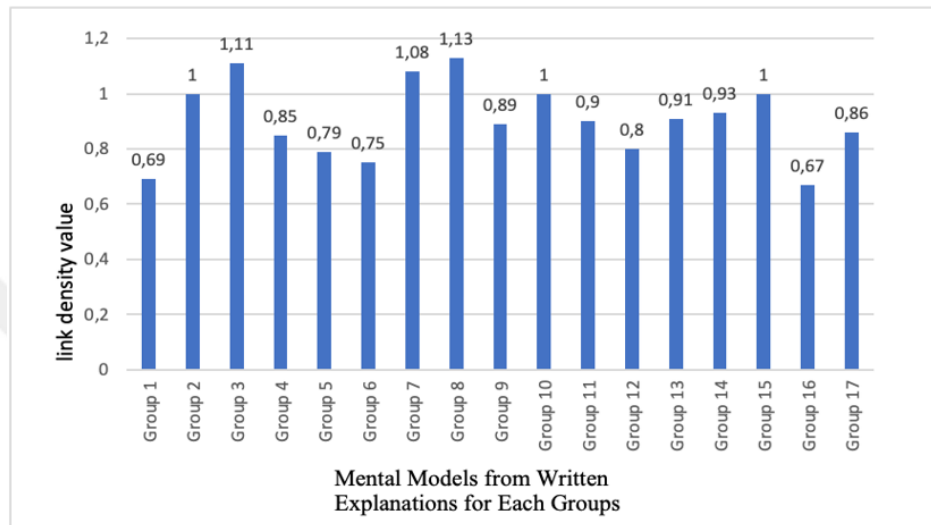
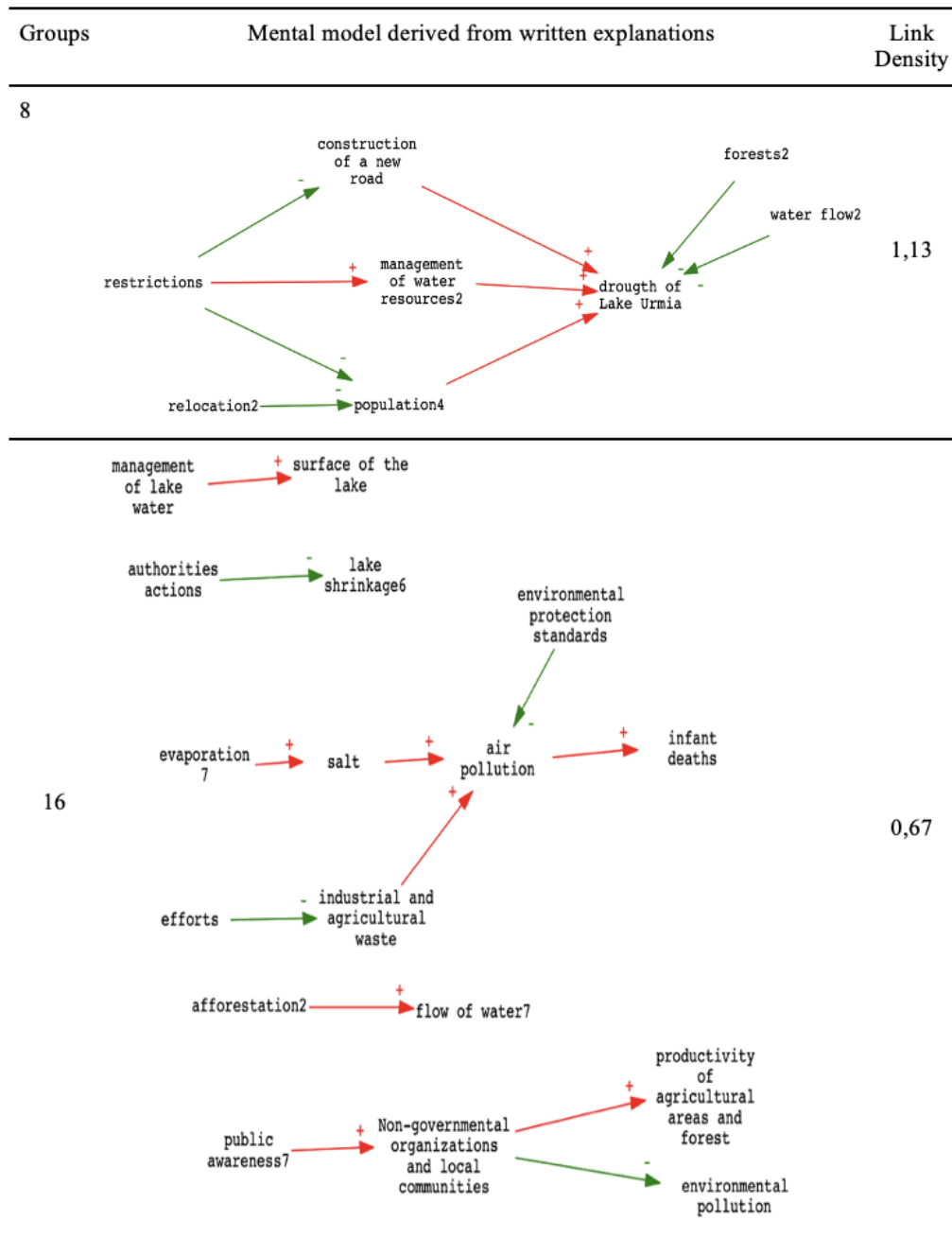


Figure 4.19. Distribution of Link Density Values among groups.

The average link density was found to be 0.90 ($n = 17$, $SD=.14$) with a minimum value of 0.67 and a maximum value of 1.13. Figure 4.20 shows the mental model representation with the highest link density and the mental model representation with the lowest link density among the results.

Group 8 connected eight variables with nine causal links within itself, while Group 16 connected 17 different variables with a total of 12 causal links as five separate connected components. Therefore, Group 8 has a high link density, while Group 16 has a low link density.



Note. Nouns indicate variables in the representations, and arrows indicate links. Red arrows represent change in the same direction, and green arrows represent change in the opposite direction.

Figure 4.20. Mental model representations with the highest and lowest link densities among the results.

Another important measure is the web-like causality index to analyze the inter-connectedness of the mental model. It is calculated as the ratio of the total number of

branching nodes to the total number of nodes. There are two types of branching nodes: nodes with more than one cause (in arrows) and nodes with more than one effect (out arrows).

Figure 4.21 shows the distribution of web-like causality values among groups. The mean value of the web-like causality index was found to be 0.230, which is considered low, ($n = 17$, $SD=.127$) with a minimum value of 0.077 and a maximum value of 0.583.

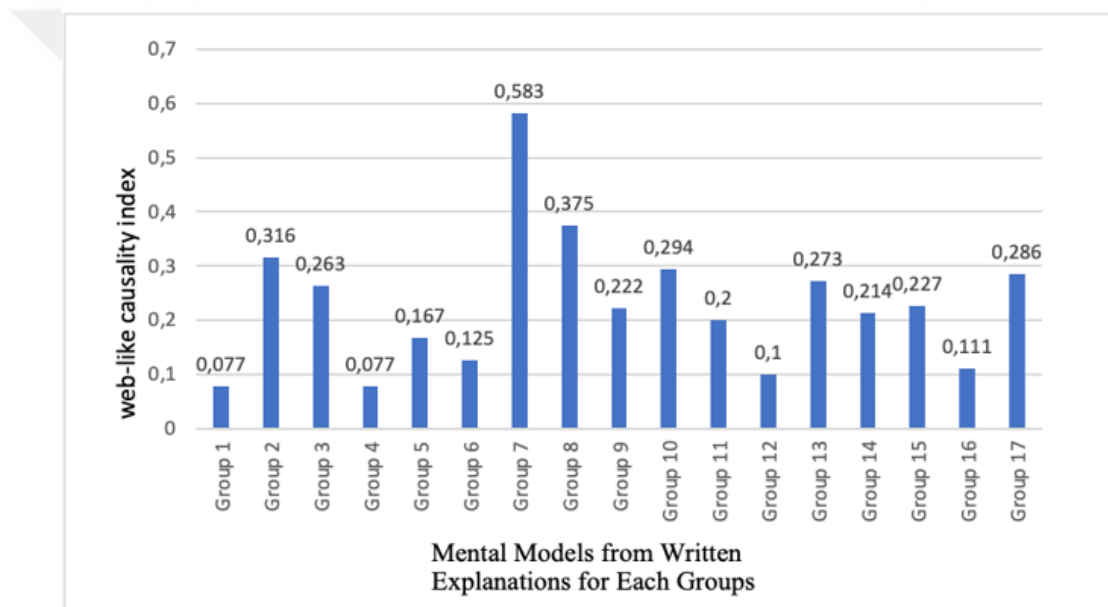
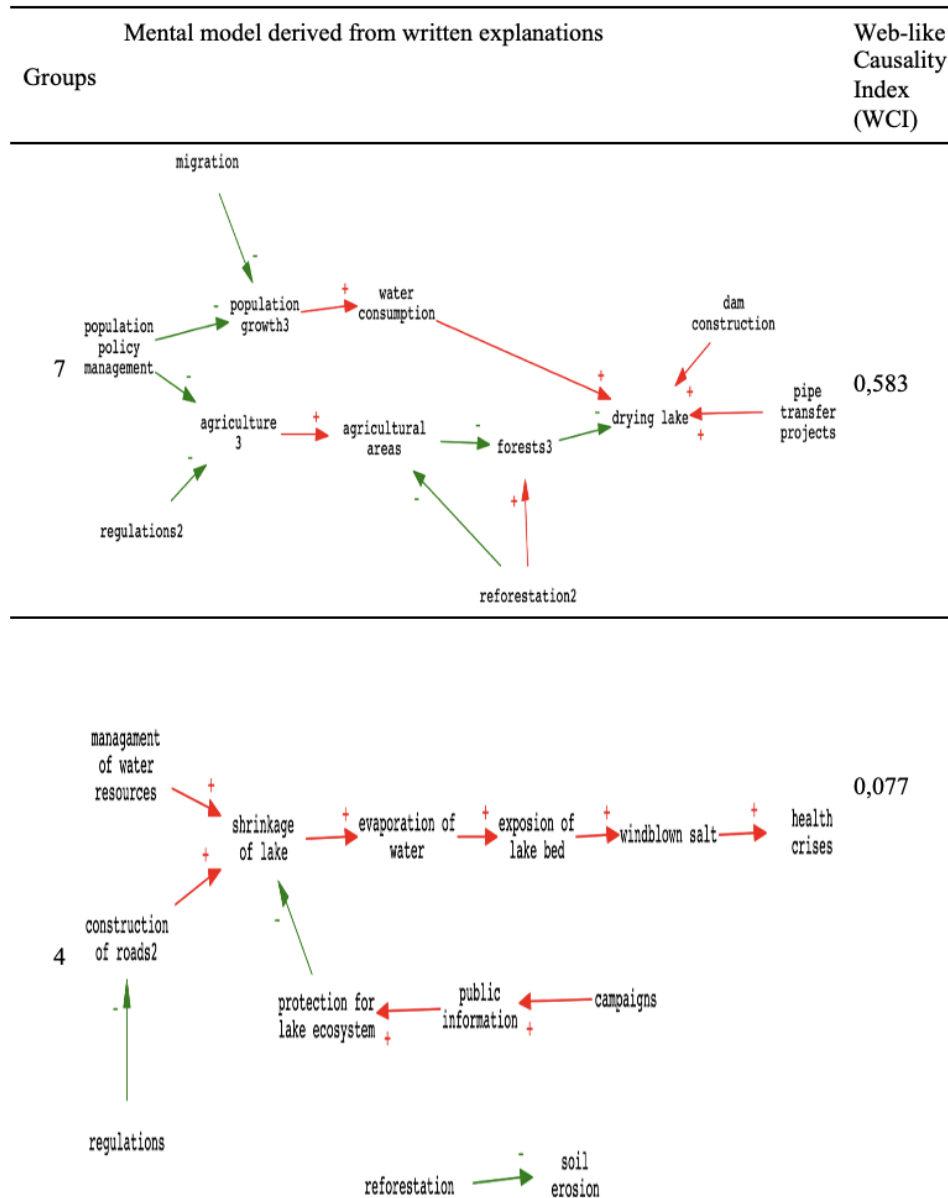


Figure 4.21. Distribution of web-like causality values among groups.

Figure 4.22 shows the mental model representations with the highest and lowest web-like causality index (WCI) among the results. Branching variables are of two types: those with more than one cause (in arrows) or those with more than one effect (out arrows). For example, in Group 4, the variable referred to as the branching variable is the shrinking of the lake, which has more than one cause. On the other hand, in Group 7, the variables referred to as branching variables are drying lake, population growth, agriculture, agricultural areas, forests, which have more than one cause; reforestation and population policy management, which have more than one effect. Overall, the results show that Group 4 has only one branching variable out of thirteen variables

and has the lowest WCI value of 0.077. In contrast, Group 7 has 7 branching variables out of twelve and has the highest WCI value of 0.583 among the representations.



Note. Nouns indicate variables in the representations, and arrows indicate links. Red arrows represent change in the same direction, and green arrows represent change in the opposite direction.

Figure 4.22. Mental model with the highest and lowest WCI among the results.

4.2.2. Feedback Loops

In order to analyze the feedback mechanism in mental model representation, the number of loops and feedback density values were determined. No feedback loop was found; therefore, the feedback density values of all groups were calculated as 0.

4.2.3. Complexity

The complexity of the mental model based on the groups' written explanations was analyzed in terms of cyclomatic complexity and causal complexity. Cyclomatic complexity was calculated using the formula $\text{Links} - \text{Nodes} + 2 \times \text{Connected Components}$. The higher the cyclomatic complexity value, the more complex the system. It was noted that if the cyclomatic complexity is higher than 10, the testability of the system may be difficult (McCabe, 1976).

Causal complexity was calculated by the formula $\text{cyclomatic complexity} \times (1 + \text{feedback density})$, which is related to cyclomatic complexity and feedback density. Since there was no feedback loop in the overall mental models, both cyclomatic and causal complexity values were found to be equal.

The distribution of cyclomatic complexity and causal complexity values for each group is illustrated in Figure 4.23. As can be observed in Figure 4.23, the values ranged between 1 and 6, with values below 10 indicating a relatively simple structure.

The mean value for cyclomatic complexity was found to be 3.18 ($n = 17$, $SD = 1.185$) with a minimum value of 1 and a maximum value of 6. Also, the mean value for causal complexity was found to be 3.18 ($n = 17$, $SD = 1.185$) with a minimum value of 1 and with a maximum value of 6.

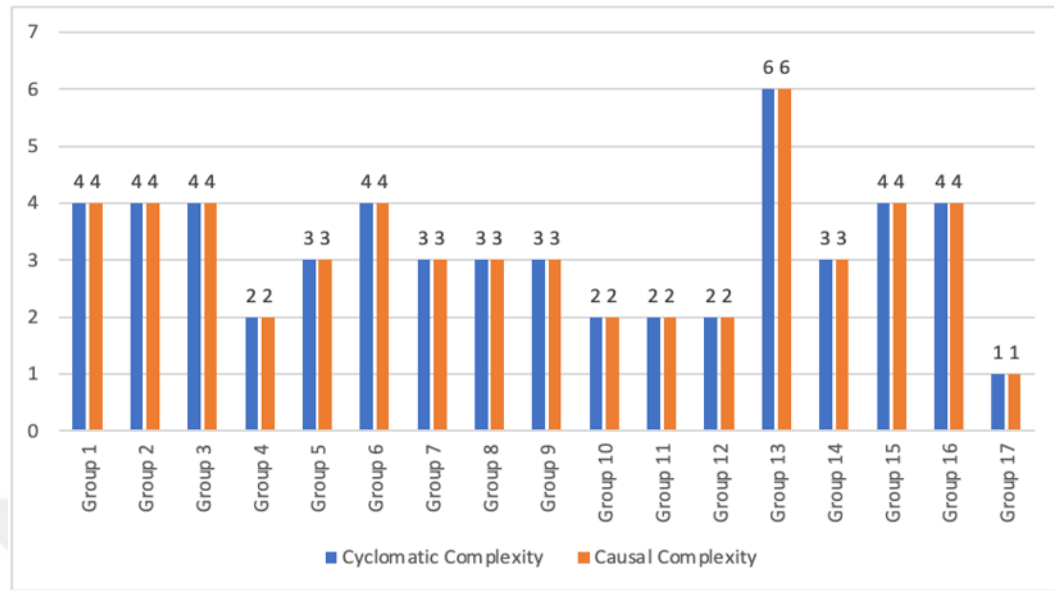
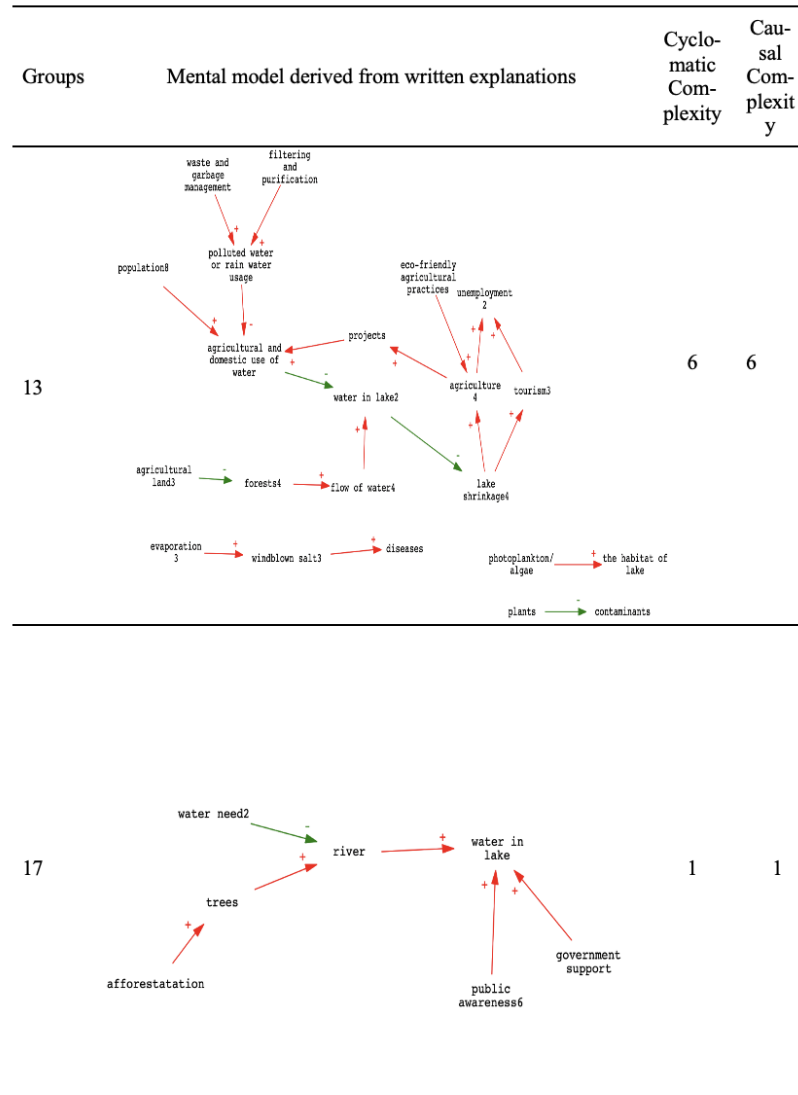


Figure 4.23. Distribution of cyclomatic complexity and causal complexity values for each group.

For a more detailed comparison, the data of the two different groups are presented in Figure 4.24. It shows the mental model with the highest and lowest cyclomatic and causal complexity. Group 13 includes a total of 22 variables and 20 causal links. This model consists of 4 separate components. When the cyclomatic complexity value was calculated, it was found to be 6. Group 17 contains 7 variables and 6 causal links in total. This model consists of only 1 component. When the cyclomatic complexity value was calculated, it was found as 1. Group 13 had the highest cyclomatic complexity value among the other groups, while Group 17 had the lowest value among the other groups. It was seen that Group 13 had a more complex structure in terms of having four separate connected components. The causal complexity of each group had the same value as cyclomatic complexity. Causal complexity is calculated using the formula $\text{cyclomatic complexity} * (1 + \text{feedback density})$ and is related to cyclomatic complexity and feedback density. Since there was no feedback loop in Group 13 and Group 17, the feedback density value was 0. As a result, the causal complexity value of Group 13 was found to be 6, and the causal complexity value of Group 17 was found to be 1. Therefore, Group 13 had the highest causal complexity value among the other groups, while Group 17 had the lowest value among the other groups.



Note. Nouns indicate variables in the representations, and arrows indicate links. Red arrows represent change in the same direction, and green arrows represent change in the opposite direction.

Figure 4.24. Mental model with the highest and lowest cyclomatic and causal complexities.

4.3. Results of the Second Research Question

Causal loop diagrams were created by each group for questions 2 and 4 in the Lake Urmia Vignette. The groups reflected their mental models by drawing causal loop diagrams. To examine the structure of the mental model derived from written explanations, several analyses were performed. Table 4.3 presented the descriptive

statistics for causal loop diagrams drawn by groups. The results indicated that the mean number of variables in causal loop diagrams was found to be 12.71 ($n = 17$, $SD = 3.177$) with a minimum value of 8 and a maximum value of 20. The mean value of the number of cause-effect relationships was found to be 15.88 ($n = 17$, $SD = 5.048$) with a minimum value of 7 and a maximum value of 26. The mean value of the number of feedback loops was found to be 2.24 ($n = 17$, $SD = 1.658$) with a minimum value of 0 and a maximum value of 6.

Table 4.3. Descriptive statistics for CLDs drawn by groups.

Criteria	Measures	<i>n</i>	<i>Mean</i>	<i>Std. Dev.</i>	<i>Min</i>	<i>Max</i>
	Total Variable	17	12.71	3.177	8	20
	Total Cause – Effect (link)	17	15.88	5.048	7	26
	# of feedback loops	17	2.47	2.124	0	7

To examine the structure of mental models systems complexity number of variable, number of cause-effect (links), number of feedback loops, link density, web-like causality, feedback density, cyclomatic complexity, and causal complexity measures were calculated. Table 4.4 shows the distribution of results of each group's causal loop diagrams according to number of variables, number of cause-effect (links), number of feedback loops, link density, web-like causality, feedback density, cyclomatic complexity, and causal complexity. The results of the possible model are also included in Table 4.4 to provide a basis for evaluation.

Table 4.4. Results of each group's drawn CLDs according to measures.

Groups	Total Variable (Node)	Total Cause-Effect (Link)	# of Feedback loops	Link Density	Web-Like Causality Index	Feed-back Density	Cyclo-matic Complexity	Causal Complexity
1	12	14	2	1.17	0.417	1.00	4.00	8.00

Table 4.4 Results of each group's drawn CLDs according to measures. (cont.)

Groups	Total Variable (Node)	Total Cause-Effect (Link)	# of Feed-back loops	Link Density	Web-Like Causality Index	Feed-back Density	Cyclo-matic Com-plexity	Causal Com-plexity
2	8	9	2	1.13	0.375	0.53	3.00	4.59
3	17	22	7	1.29	0.529	1.00	7.00	14.00
4	13	17	0	1.31	1.000	0.00	8.00	8.00
5	14	16	3	1.14	0.357	0.63	4.00	6.53
6	13	15	3	1.15	0.308	1.00	4.00	8.00
7	12	18	0	1.50	0.500	0.00	8.00	8.00
8	15	17	4	1.13	0.267	1.00	4.00	8.00
9	8	7	0	0.88	0.111	0.00	1.00	1.00
10	20	21	3	1.05	0.300	0.34	3.00	4.02
11	12	14	0	1.17	0.500	0.00	4.00	4.00
12	12	13	2	1.08	0.250	0.84	3.00	5.52
13	11	23	6	2.09	0.917	0.59	14.00	22.24
14	12	14	4	1.17	0.333	1.0	4.00	8.00
15	13	14	2	1.08	0.231	0.6	3.00	4.67
16	16	26	4	1.63	0.750	0.20	12.00	14.34
17	8	10	0	1.25	0.500	0.00	4.00	4.00
Expert CLD	22	31	13	1.41	0.545	1.00	11.00	22.00

In addition, the mental model of each group based on causal loop diagrams, including measures were also presented in Figure 4.25-Figure 4.41. The researcher revised these models based on the causal loop diagrams drawn by the groups and transferred to Vensim. When revising the models, great attention was paid to avoiding data loss. The first step was to identify variables that had the same meaning or were expressed in the same way. This stage aimed to accurately determine the number of variables and to avoid counting the same variable twice. A process of how the causal loop diagrams drawn by Group 6 were transferred into the Vensim software

was provided (Appendix G) The first drawing of Group 6 shows the problem, and the second one shows how to solve the problem. Especially in the second one, the group redrew the causal loops to show the problem and proposed a solution by adding new variables to the variables of the first one. The researcher transformed this into a single model by keeping the common variables while transferring it to Vensim software. Since no problems with causality were detected, polarity was represented as indicated by Group 6.

As seen in Figure 4.25-Figure 4.41, most of the groups could draw the variables in closed loops; some of these loops include the whole model, and some of them form part of the model. However, it can be seen that they were able to draw causal loops in general. The groups were also able to identify the polarity of the causality. Green arrows represent negative (opposite direction) causality, while red arrows represent positive (same direction) causality.

Variables and links where the causality between variables was considered controversial were colored grey. For example, in Group 1, the polarity of the link between diseases and public awareness is shown as negative causality. However, this should be interpreted as positive causality. An increase in disease leads to increased public awareness, representing the same directional relationship. As a result, this link is greyed out as it is considered incorrectly drawn.

The detailed results for each measure will be explained under the subheadings interconnection, feedback, and complexity.

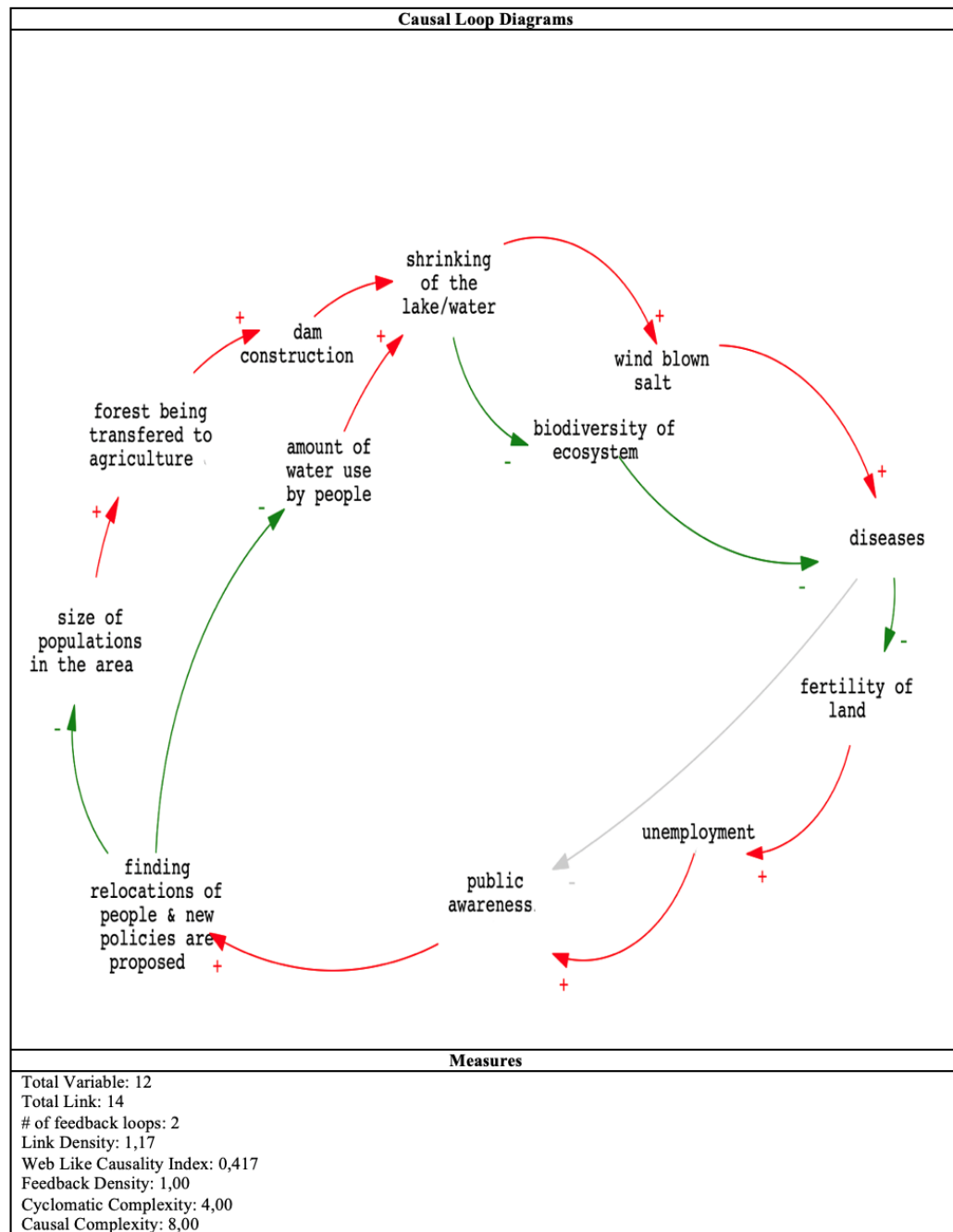


Figure 4.25. Mental models derived from causal loop diagrams for group 1.

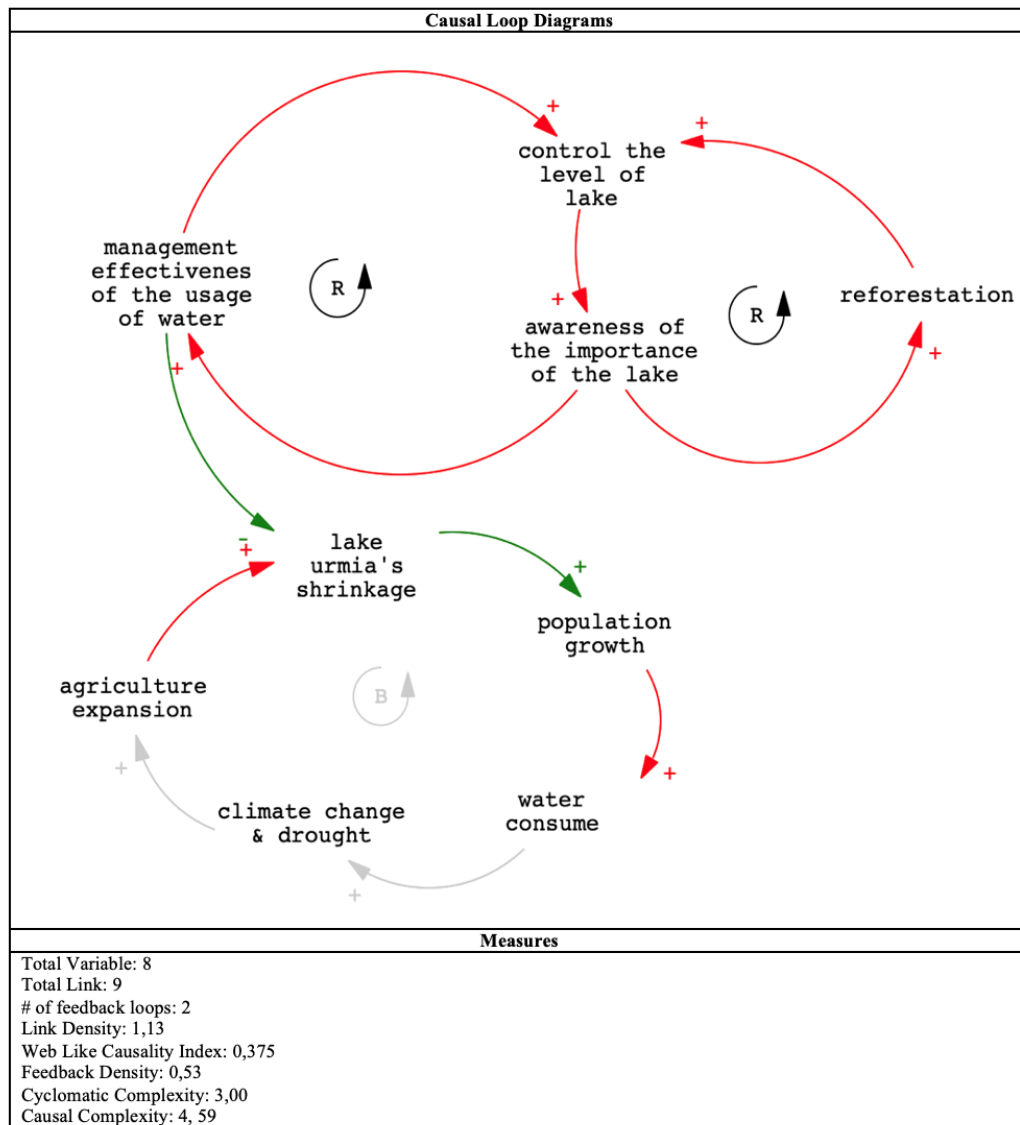


Figure 4.26. Mental models derived from causal loop diagrams for group 2.

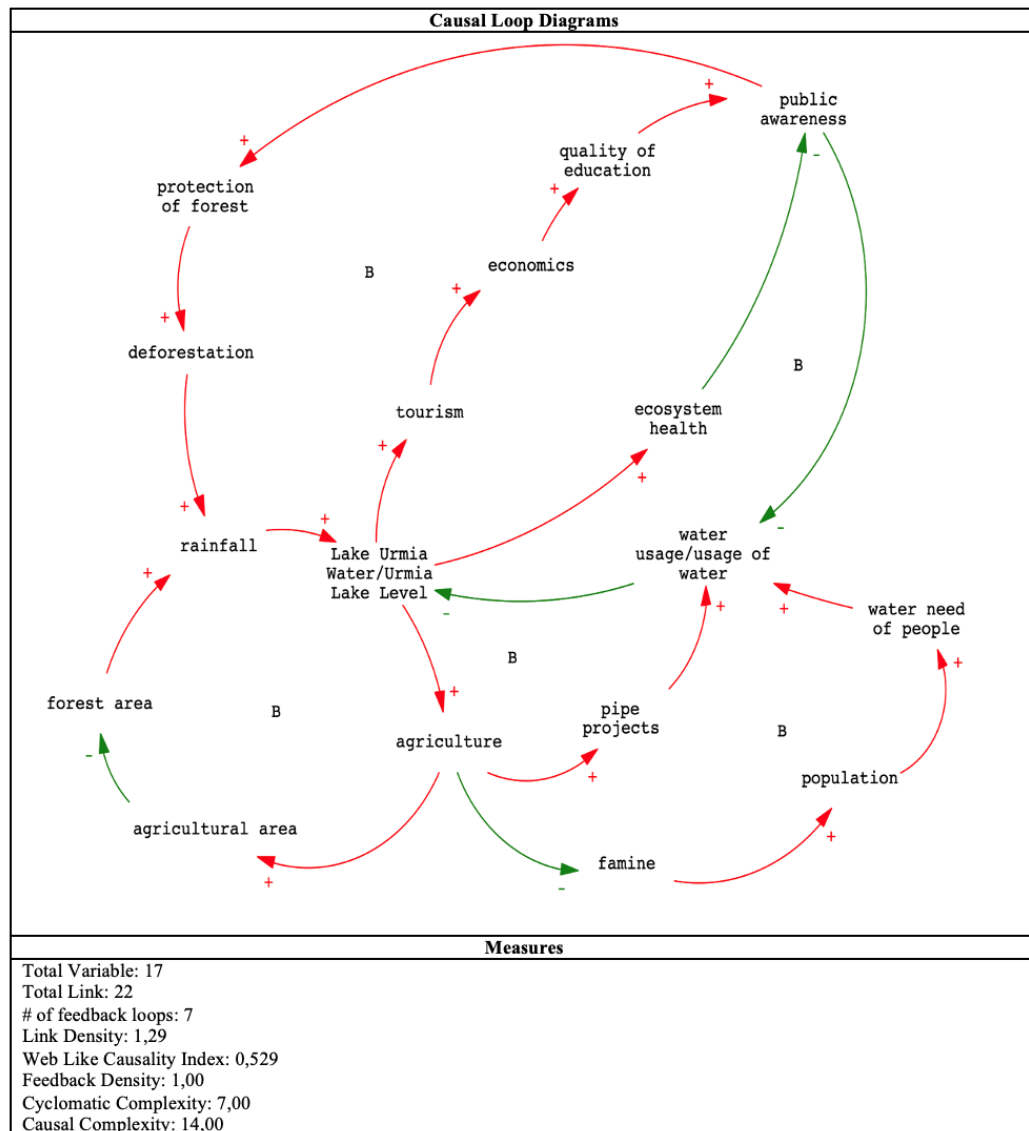


Figure 4.27. Mental models derived from causal loop diagrams for group 3.

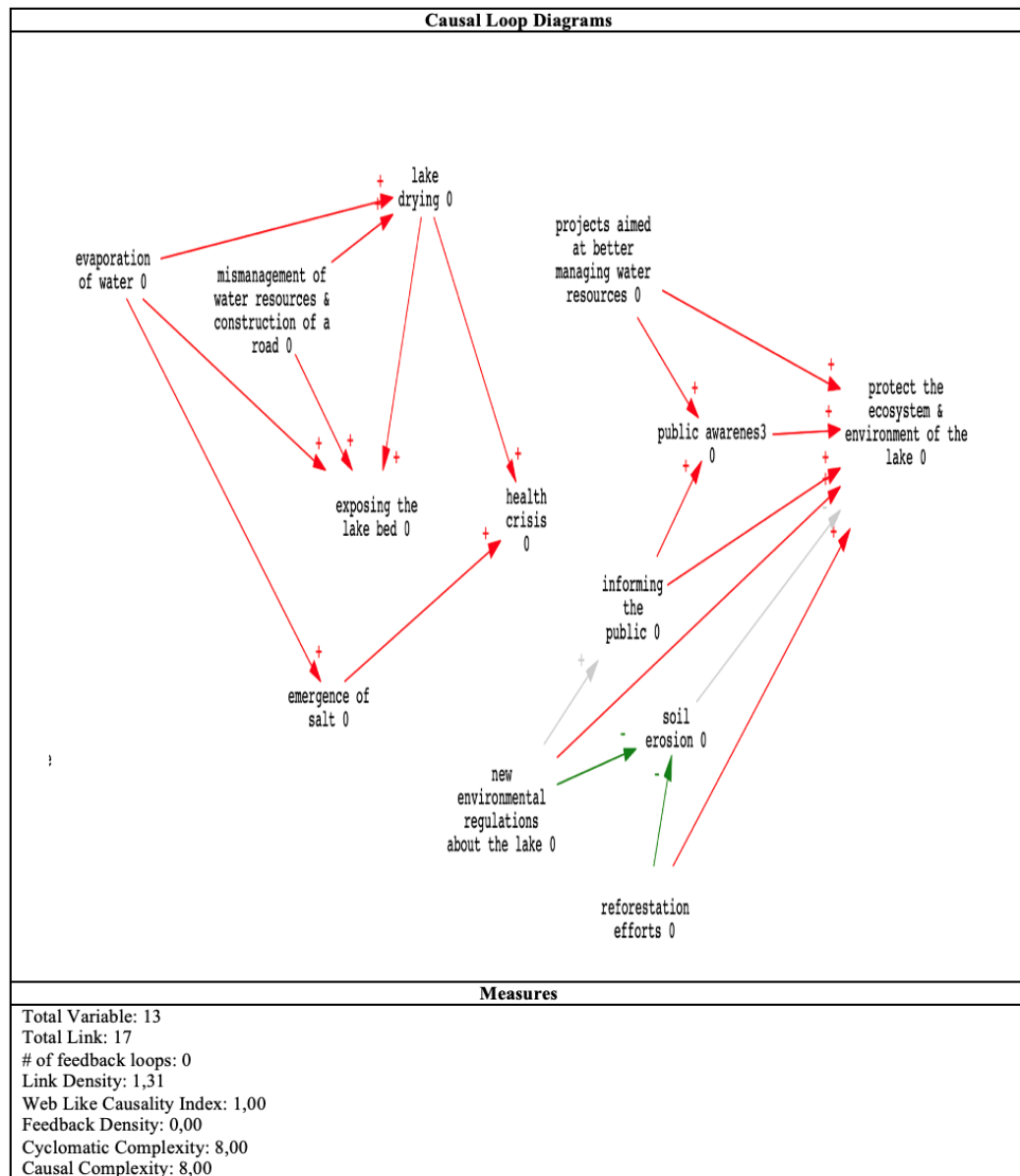


Figure 4.28. Mental models derived from causal loop diagrams for group 4.

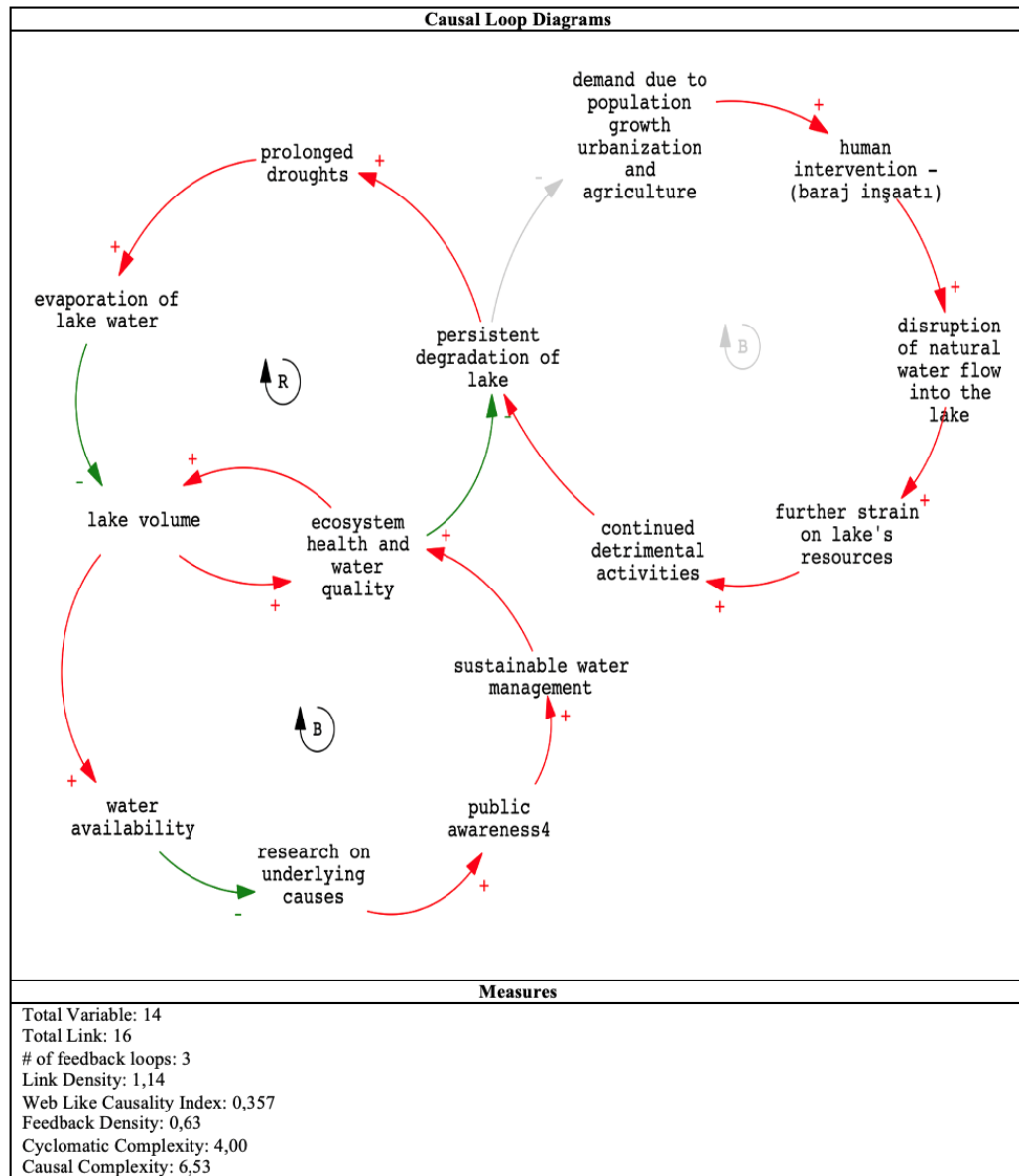


Figure 4.29. Mental models derived from causal loop diagrams for group 5.

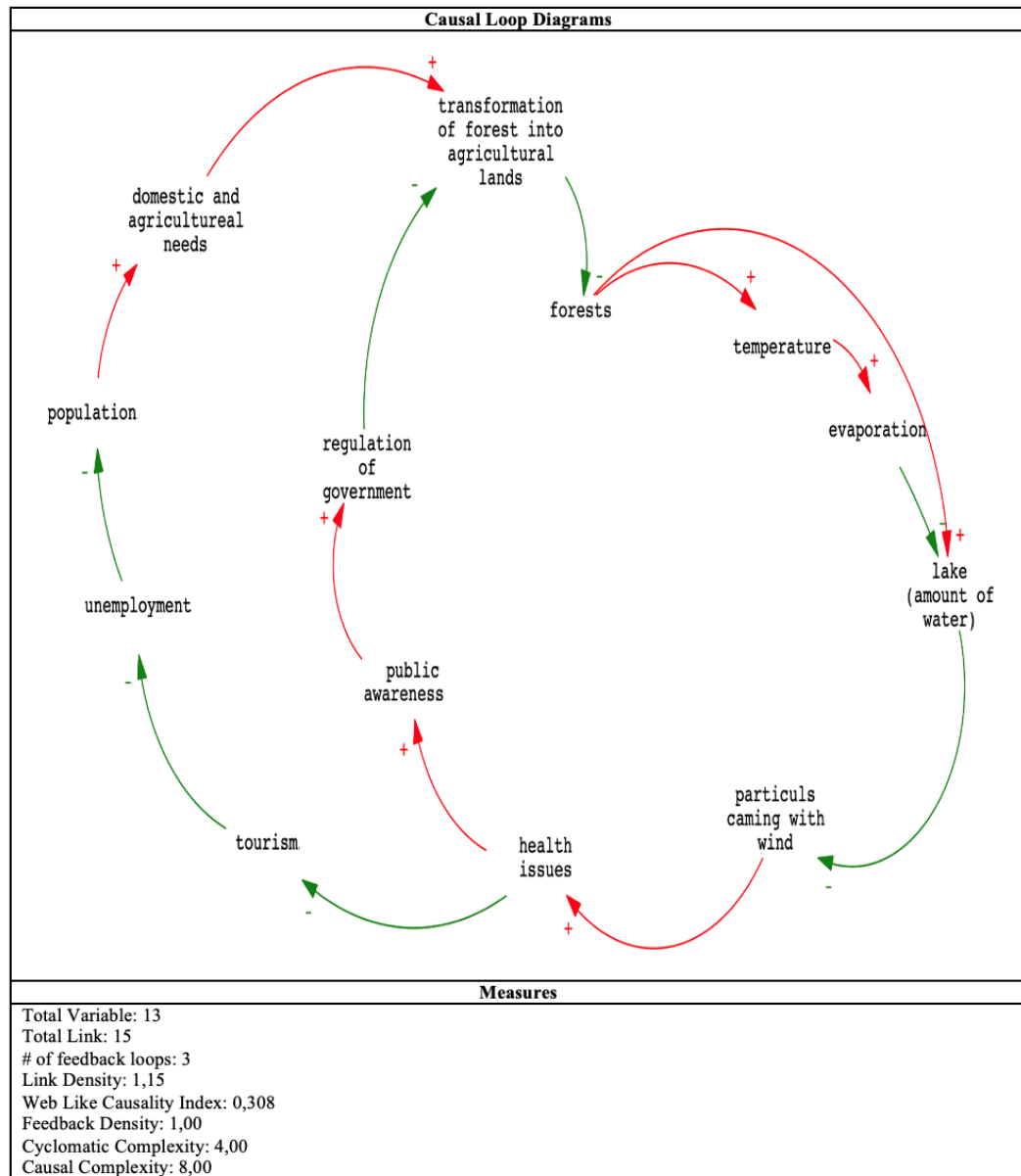


Figure 4.30. Mental models derived from causal loop diagrams for group 6.

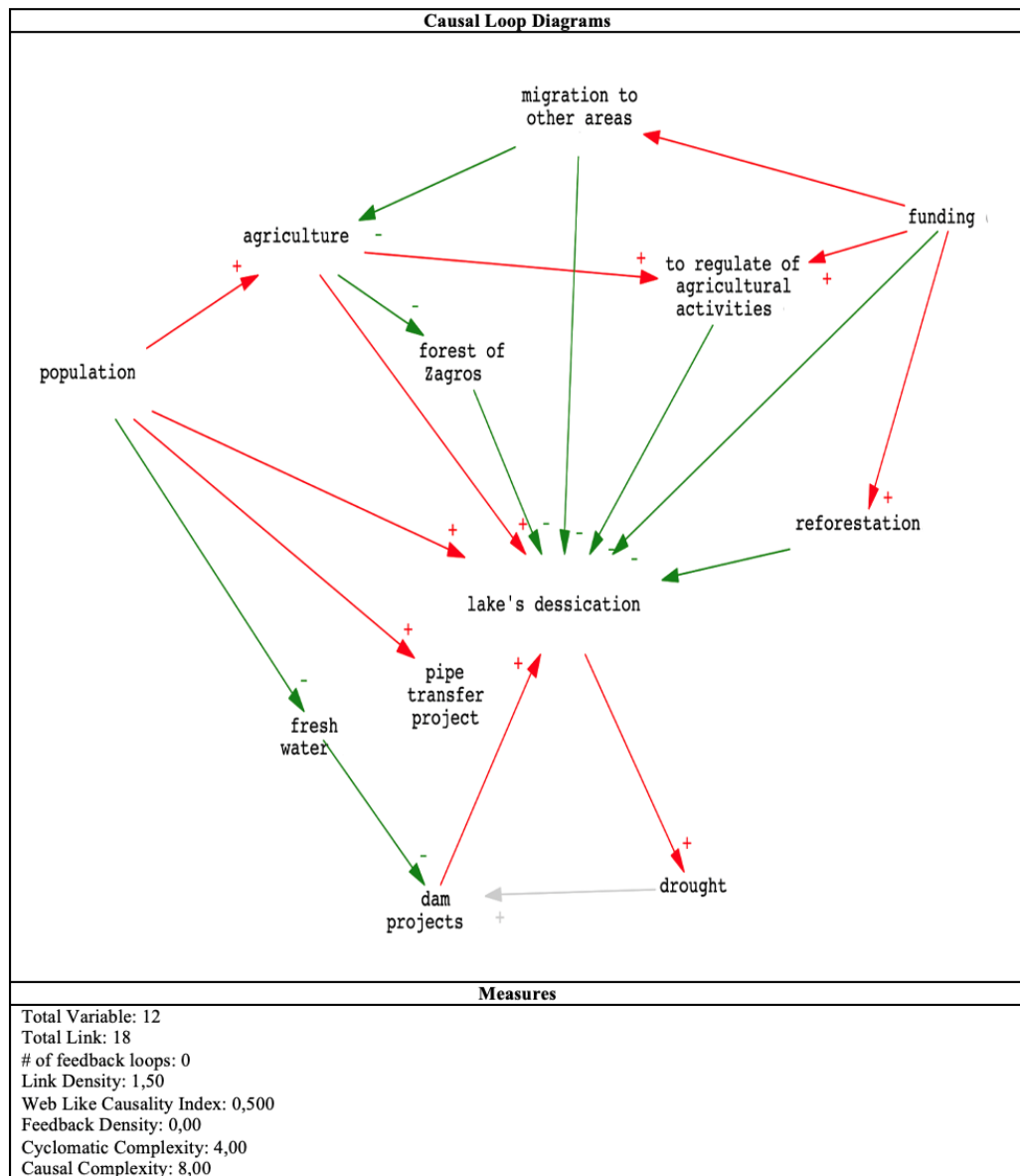


Figure 4.31. Mental models derived from causal loop diagrams for group 7.

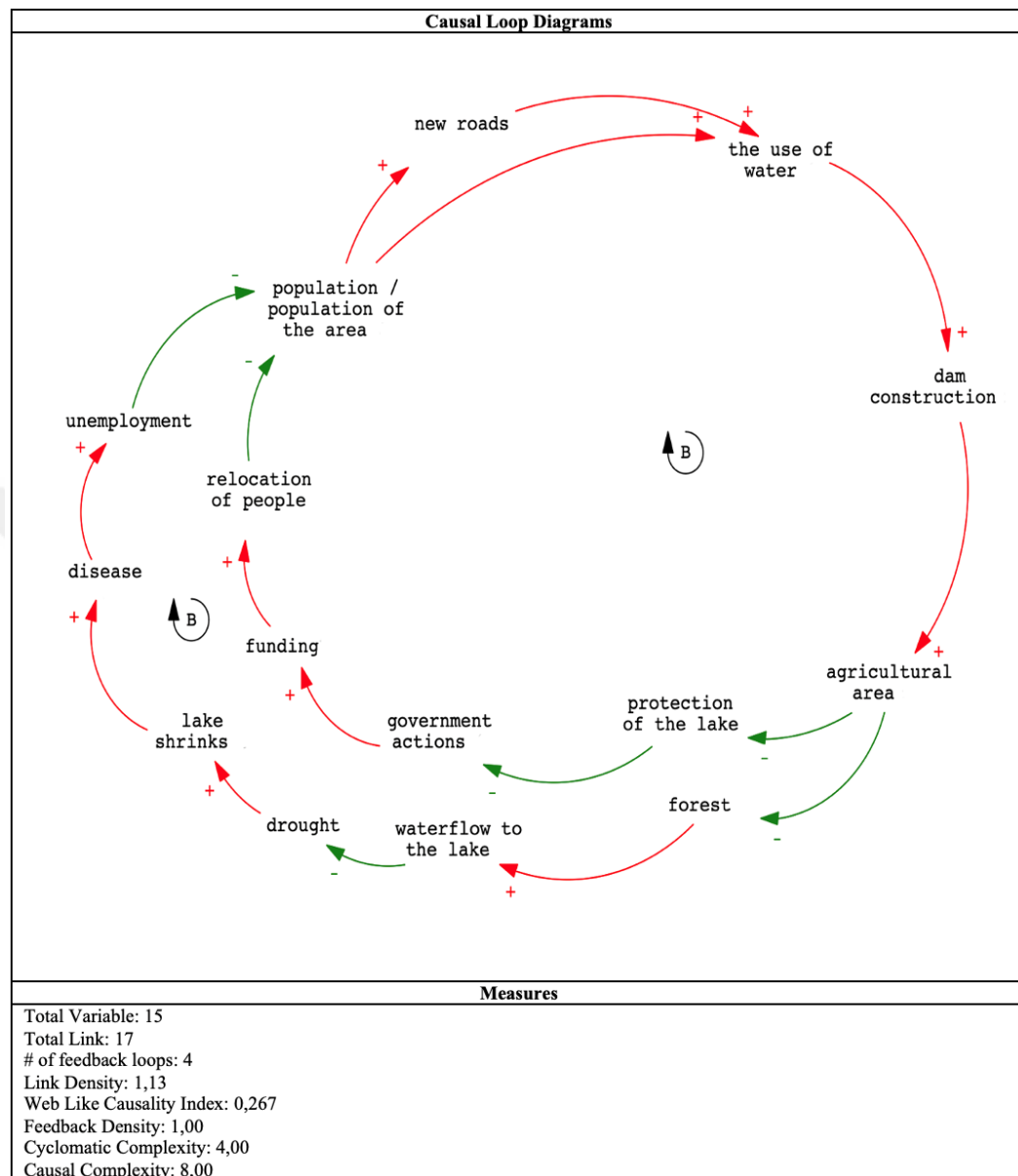


Figure 4.32. Mental models derived from causal loop diagrams for group 8.

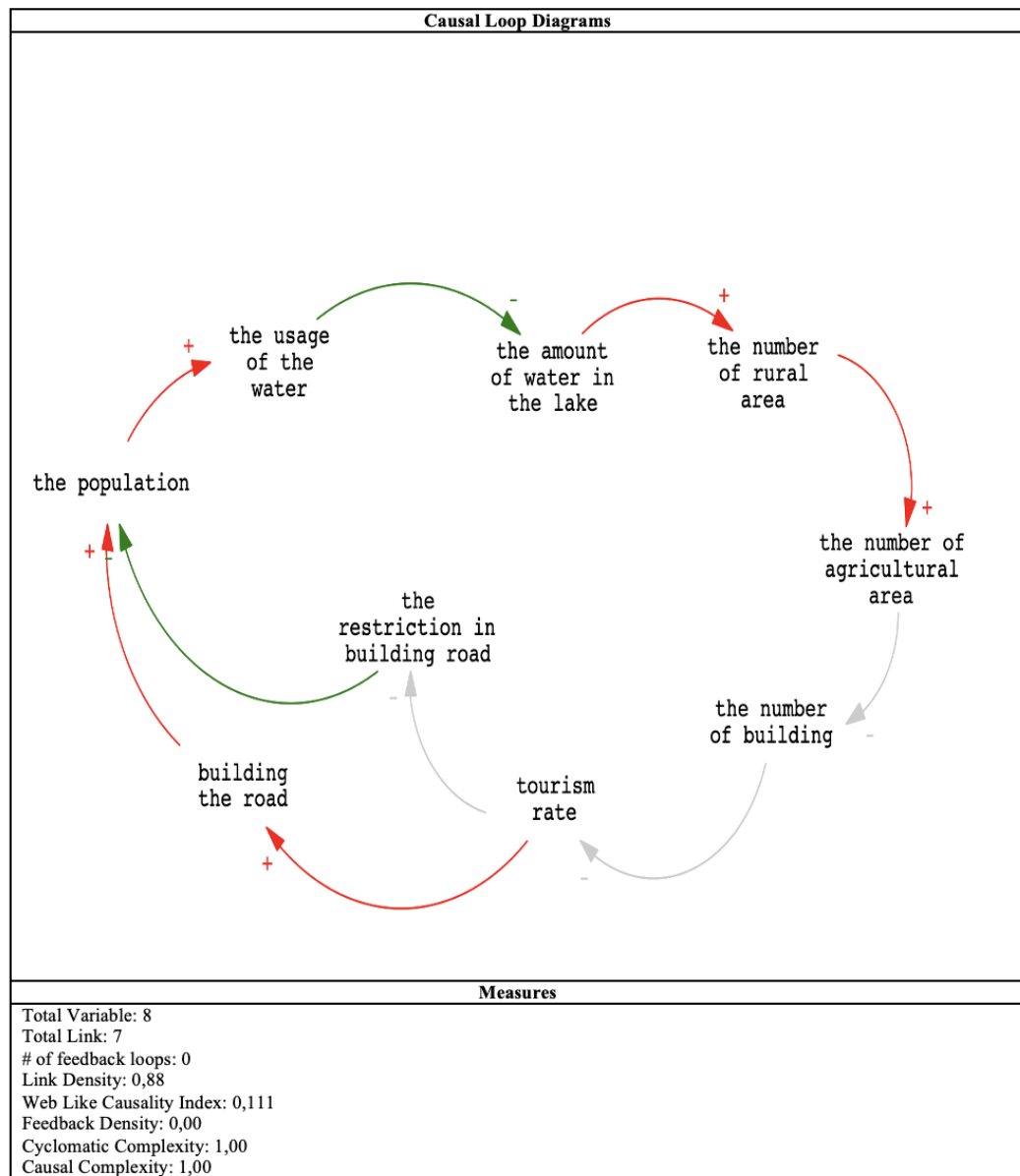


Figure 4.33. Mental models derived from causal loop diagrams for group 9.

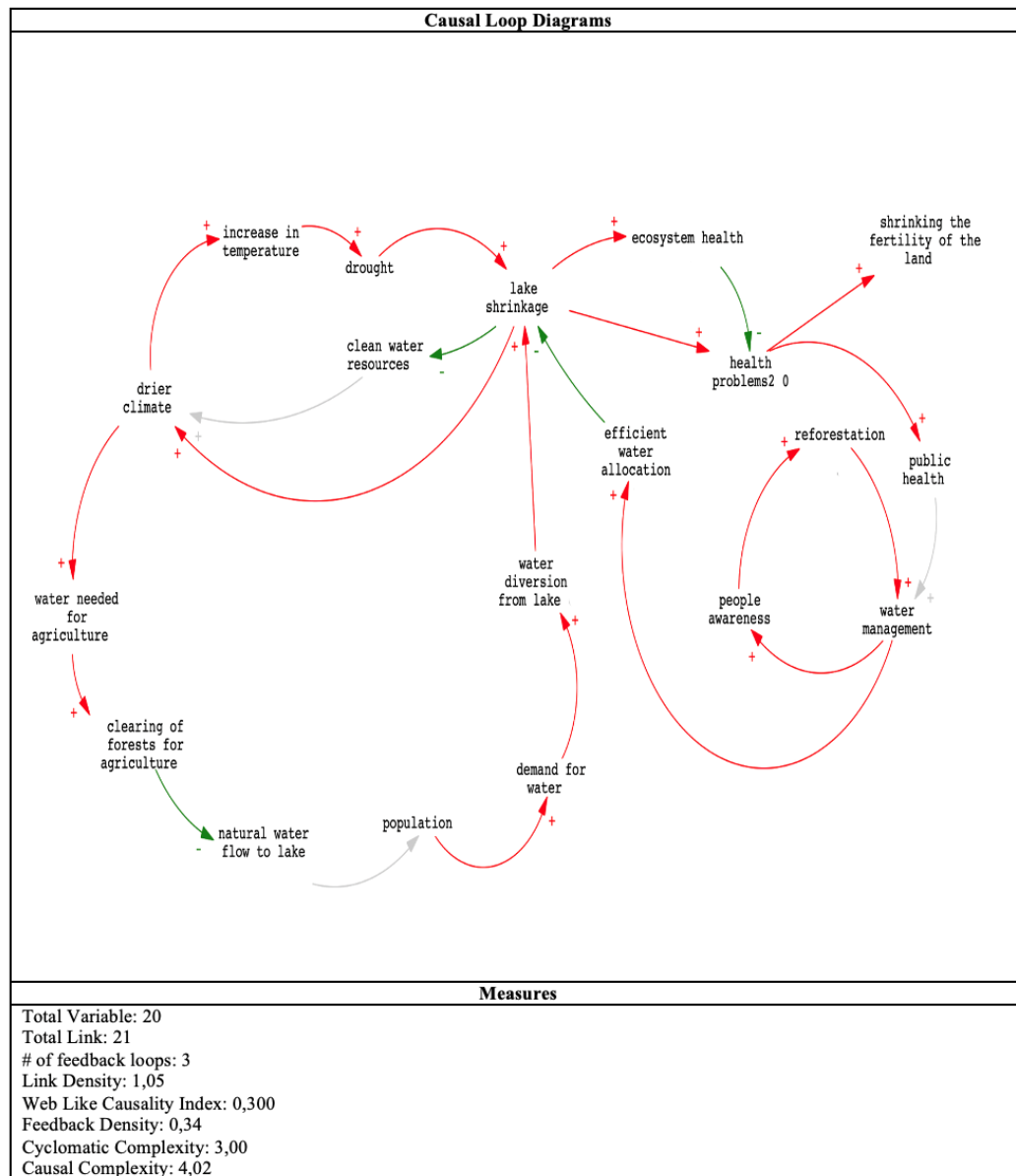


Figure 4.34. Mental models derived from causal loop diagrams for group 10.

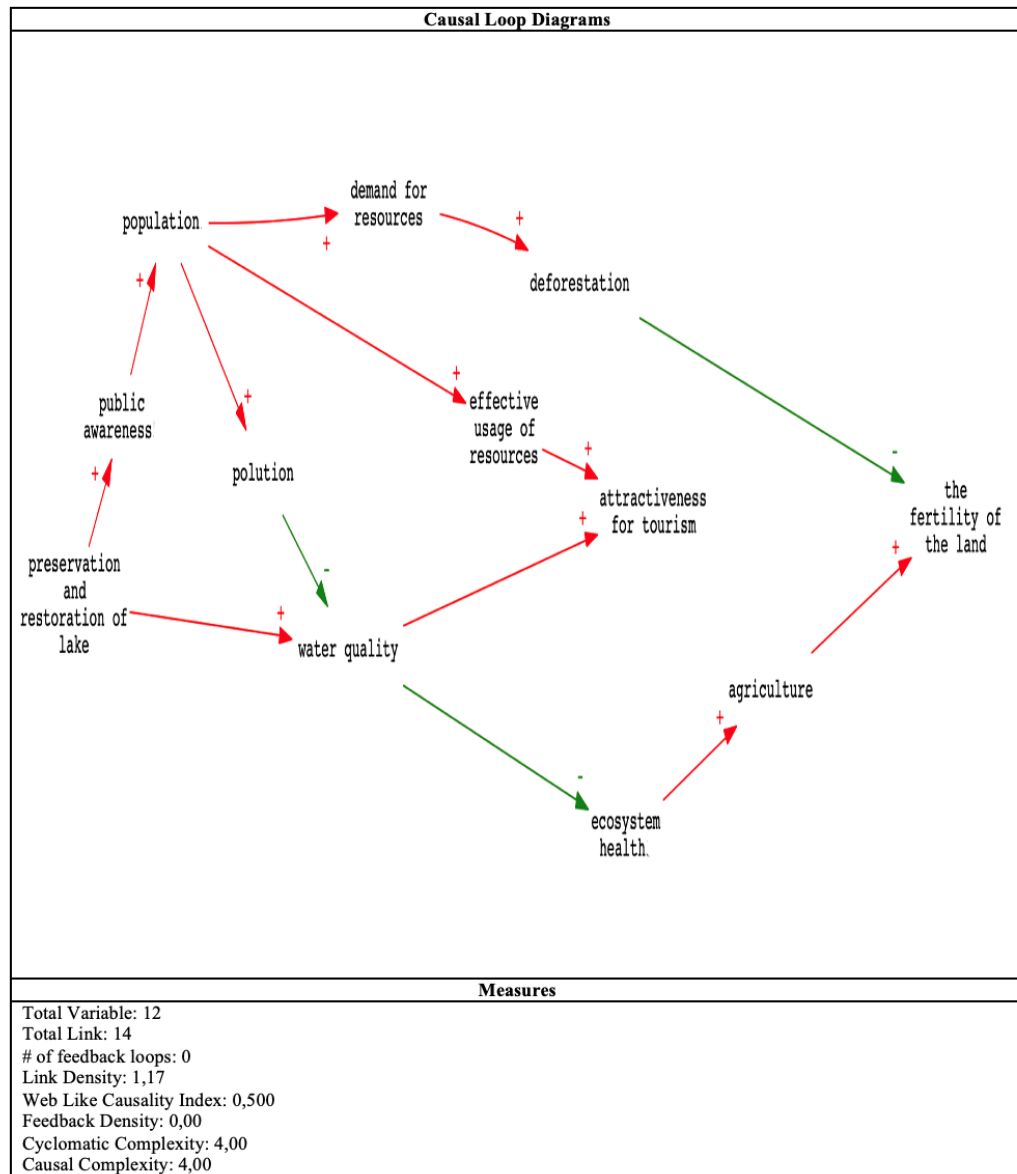


Figure 4.35. Mental models derived from causal loop diagrams for group 11.

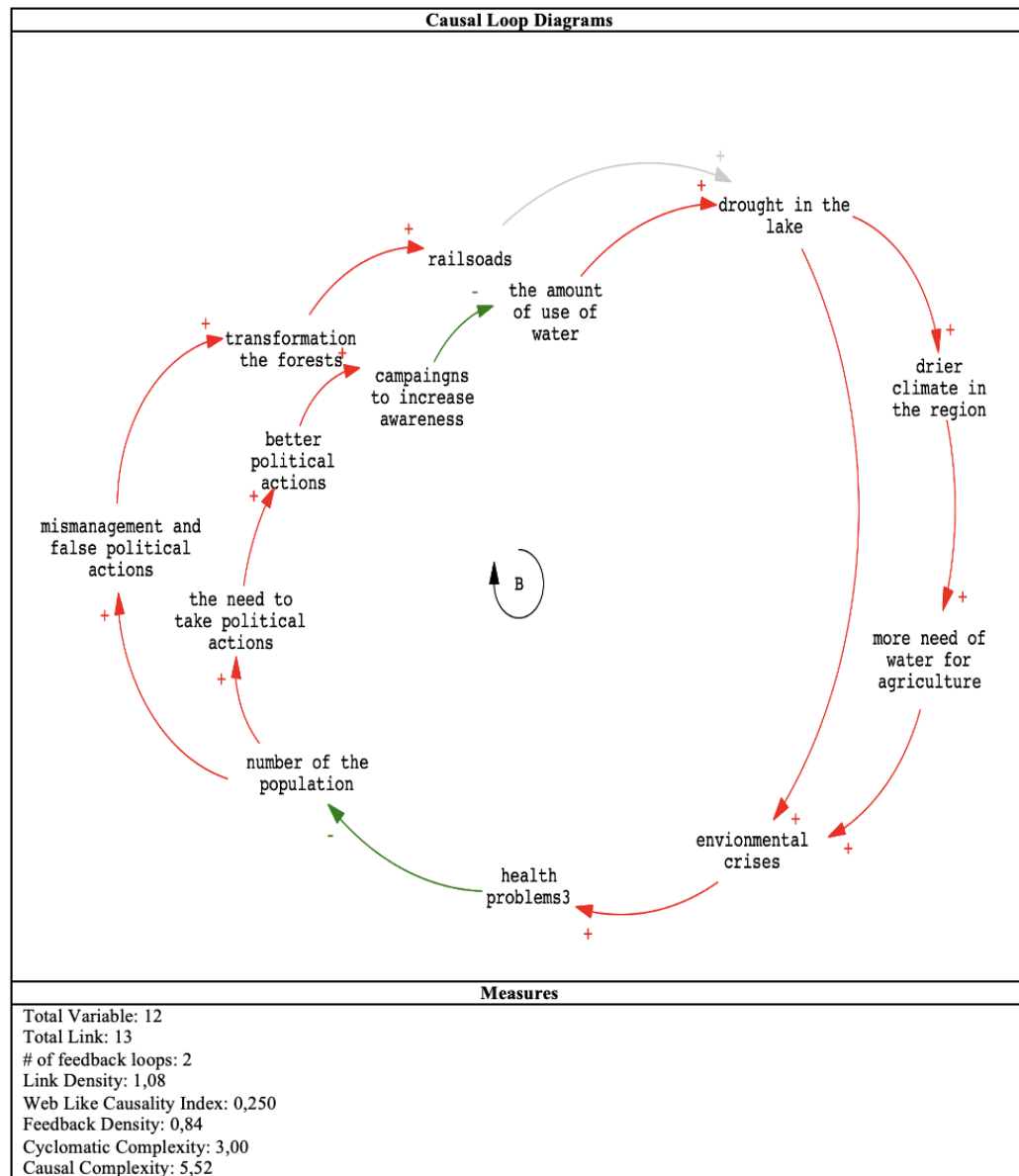


Figure 4.36. Mental models derived from causal loop diagrams for group 12.

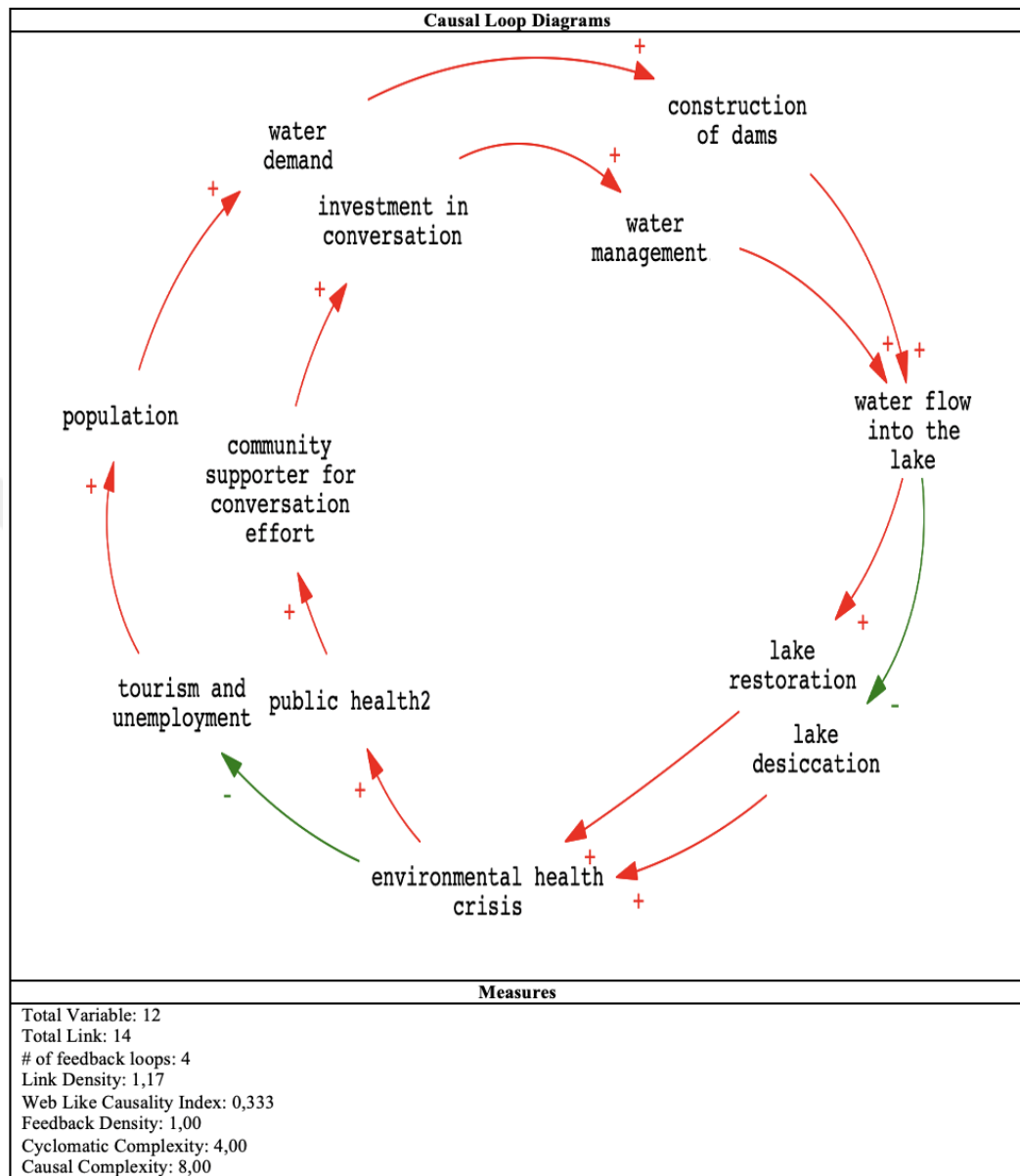


Figure 4.38. Mental models derived from causal loop diagrams for group 14.

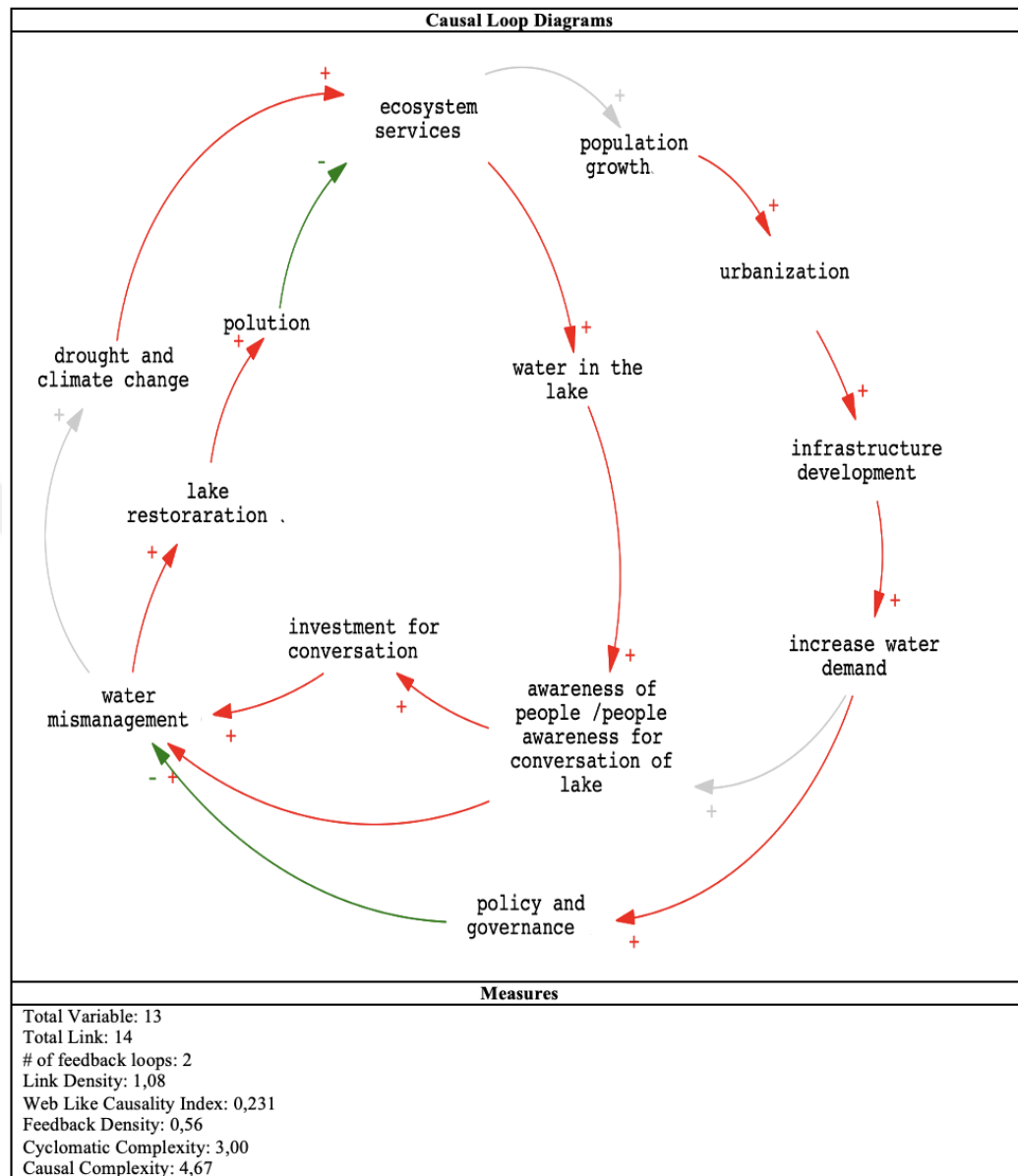


Figure 4.39. Mental models derived from causal loop diagrams for group 15.

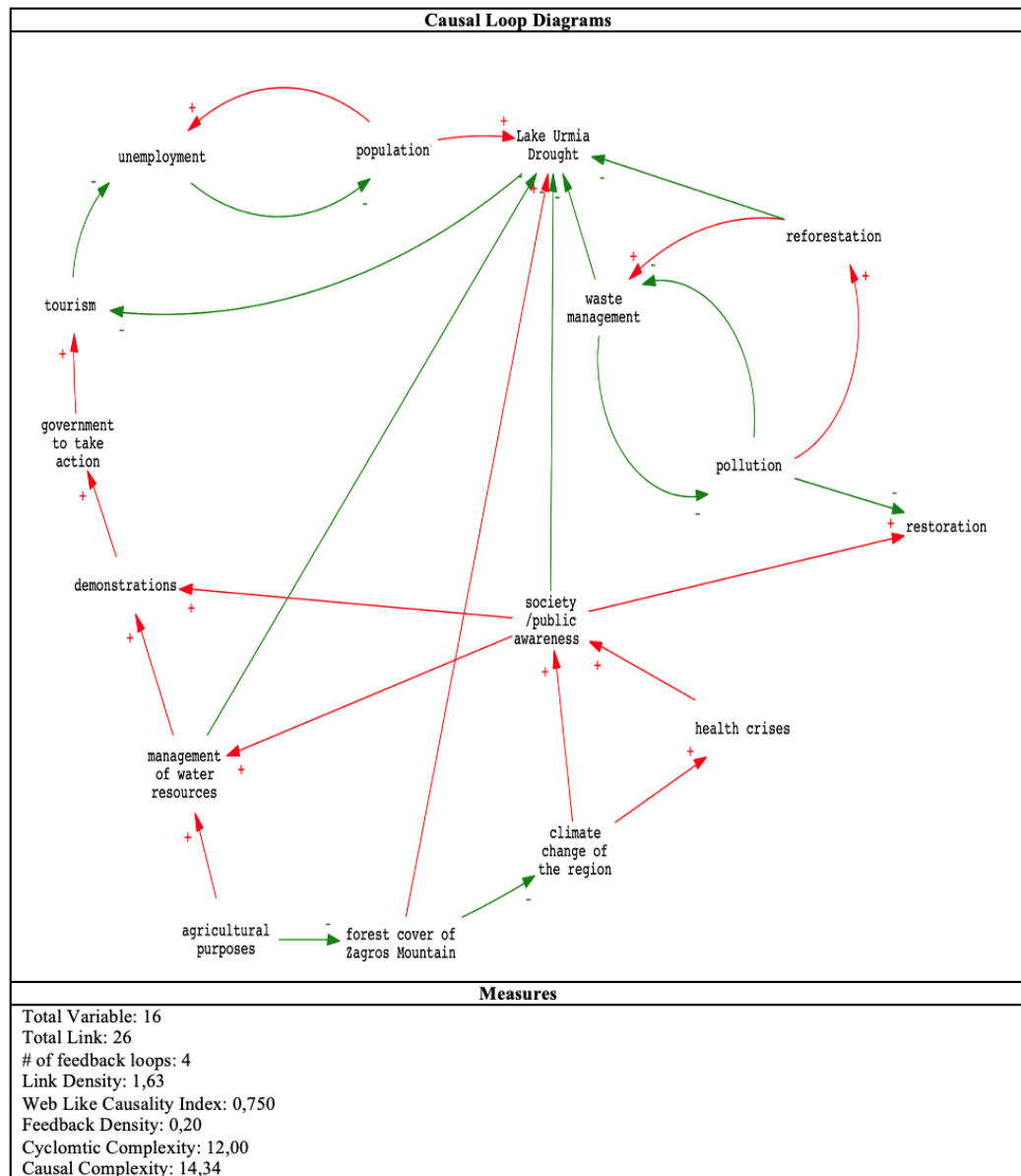


Figure 4.40. Mental models derived from causal loop diagrams for group 16.

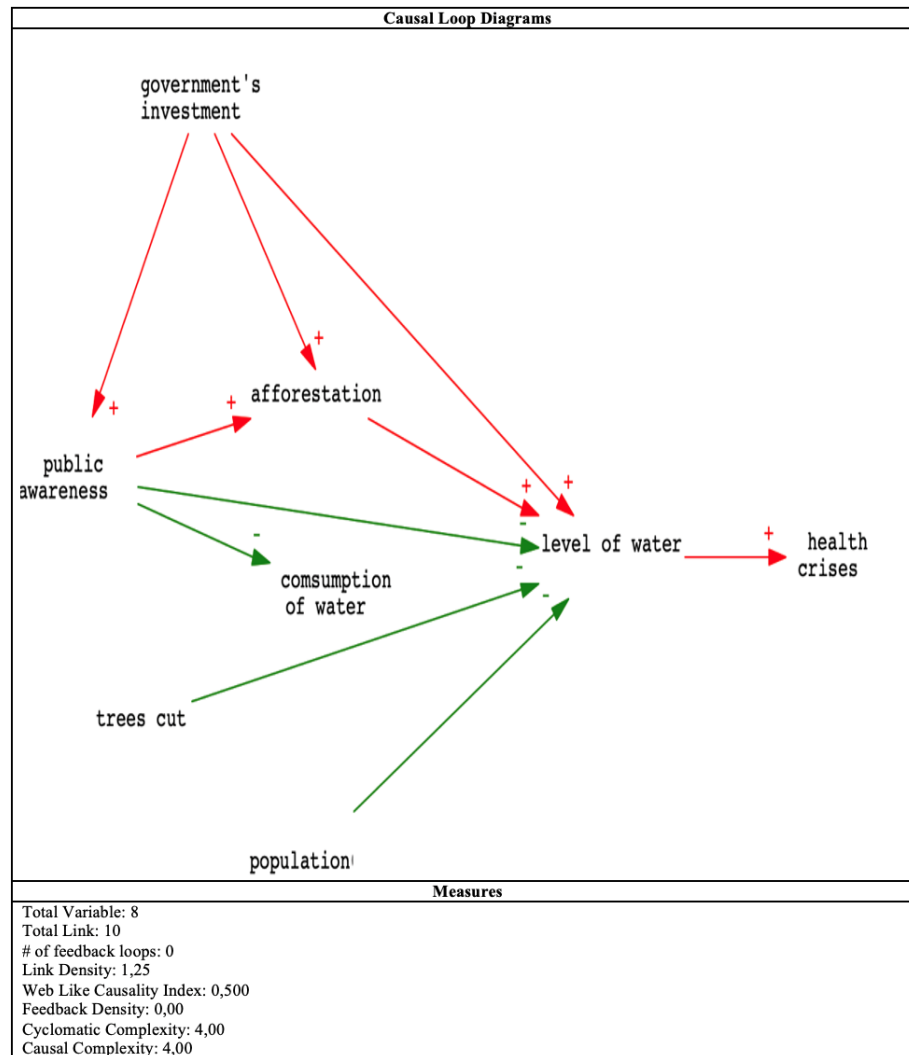


Figure 4.41. Mental models derived from causal loop diagrams for group 17.

4.3.1. Interconnection

Interconnections of causal loop diagrams were examined regarding link density and web-like causality index. Link density was calculated to measure the interconnectedness of the mental models. It is the ratio of the number of links to the number of nodes in a representation. A value greater than 1 means that the number of links is greater than the number of variables (nodes), while a value less than 1 means that the number of variables (nodes) is greater than the number of links.

As seen in Figure 4.42, 16 groups have a link density greater than 1. This shows that by drawing a causal loop diagram, most groups could make more connections between variables.

The mean value of link density was found to be 1.25 ($n = 17$, $SD = .277$), with a minimum value of .88 and a maximum value of 2.09.

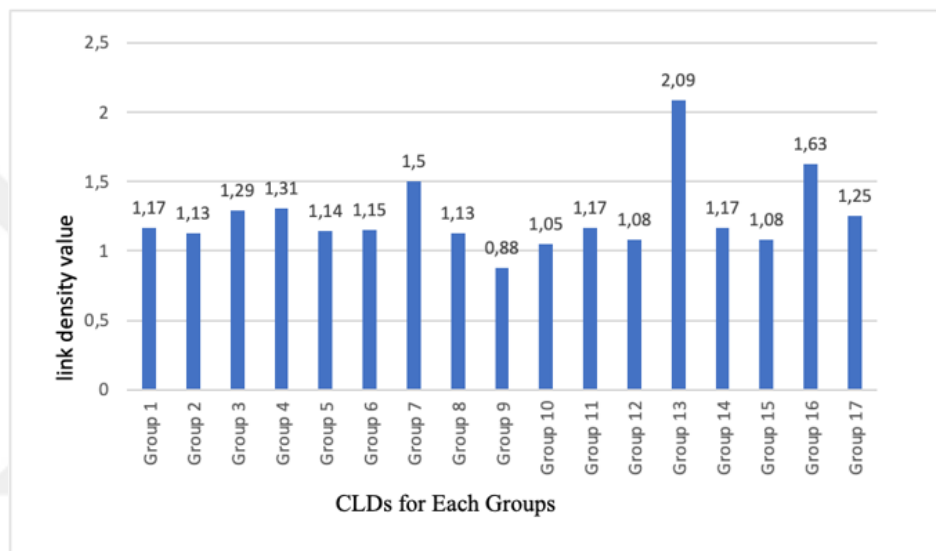


Figure 4.42. Distribution of Link Density values among groups.

Figure 4.43 shows the causal loop diagrams with the highest and lowest link density levels among the results. Among all groups, Group 9 has the lowest link density value (0.88), and Group 13 has the highest link density value (2.09). In the unrevised causal loop diagram of Group 9, there were eight variables and nine links, and the link density was 1.11. However, when the quality of the causality was analyzed, one variable and three links between were colored grey, reducing the link density to .88. For example, the positive link between the number of buildings and the tourism rate (the number of buildings $\rightarrow$ tourism rate) has been removed as it is considered a controversial causality, and more information is needed for it to be accepted as causality. On the other hand, in the unrevised causal loop diagram of Group 13, there were eleven variables and twenty-six links, and the link density was 2.36. However, when the quality of causality between variables was analyzed, three links were colored grey, reducing the

link density to 2.09. For example, the positive link between forest/forestation and population (forest/forestation $\rightarrow$ population) has been removed as it is considered a controversial causality. More information is needed to accept how forest/afforestation causes a positive change in the population. The negative link between (population $\rightarrow$ forest/forestation) has been retained because a population increase may lead to a decrease in forest/forestation.

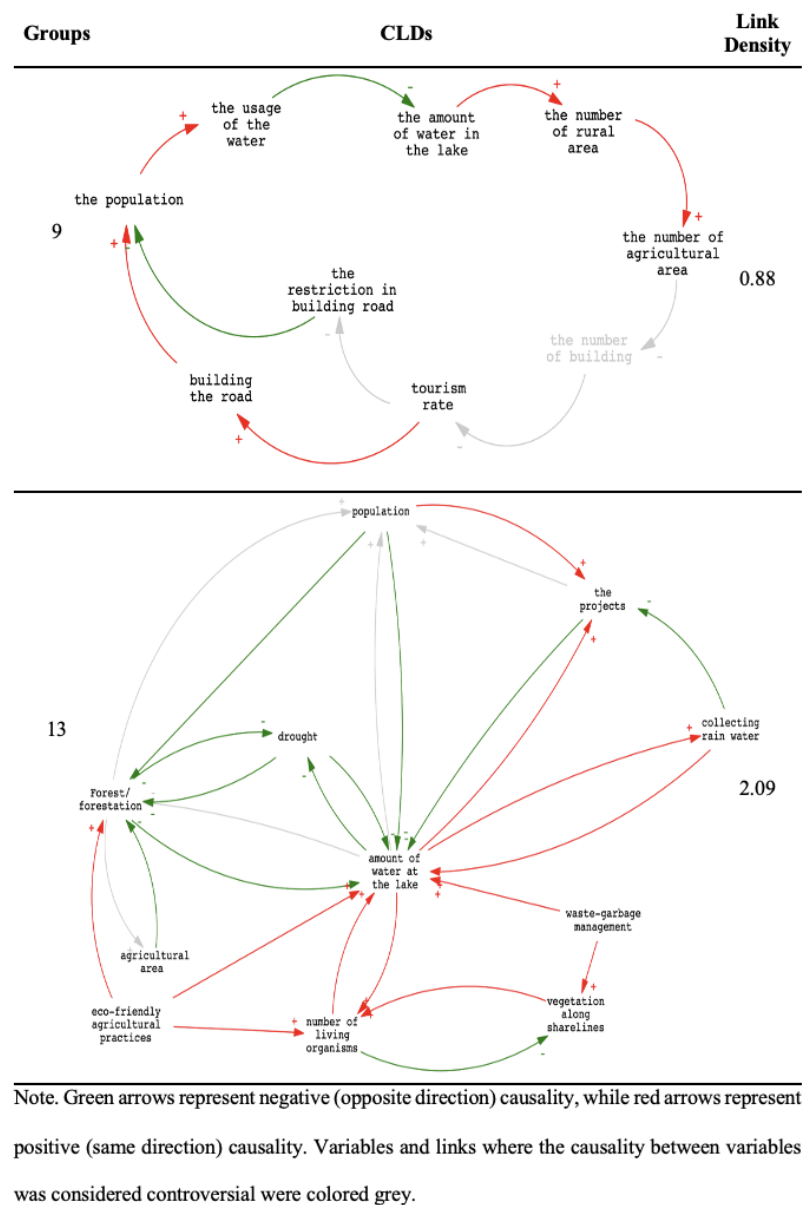


Figure 4.43. CLDs with the highest and lowest link densities among the groups.

Another important measure is the web-like causality index to analyze the inter-connectedness of the causal loop diagrams. It is calculated as the ratio of the total number of branching nodes to the total number of nodes in the causal loop diagrams. There are two types of branching nodes: nodes with more than one cause (in arrows) and nodes with more than one effect (out arrows).

The distribution of web-like causality index among groups was provided in Figure 4.44. According to the results, the mean value of the web-like causality index for all groups was found to be .450, which can be considered as close to moderate ($n = 17$, $SD = 0.241$) with a minimum value of .111 and a maximum value of 1.00.

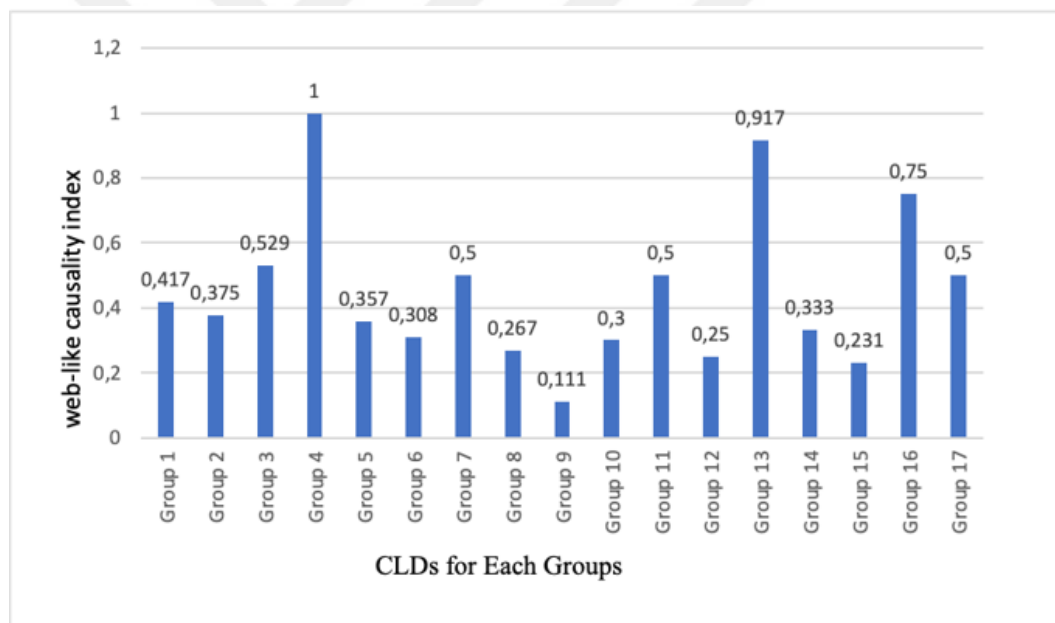


Figure 4.44. Distribution of web-like causality values among groups.

Figure 4.45 showed causal loop diagrams with the highest and lowest web-like causality index among the groups. Group 9 contains eight variables (nodes) in their causal loop diagram and has only one branching node, which is the population, therefore, the web-like causality index was found to be 0.111, which is the lowest value among the results.

Group 4 has the highest number of branching variables, with seven variables having more than one effect and six variables having more than one cause. Therefore, the web-like causality index was found to be 1.00, which is the highest value among the groups.

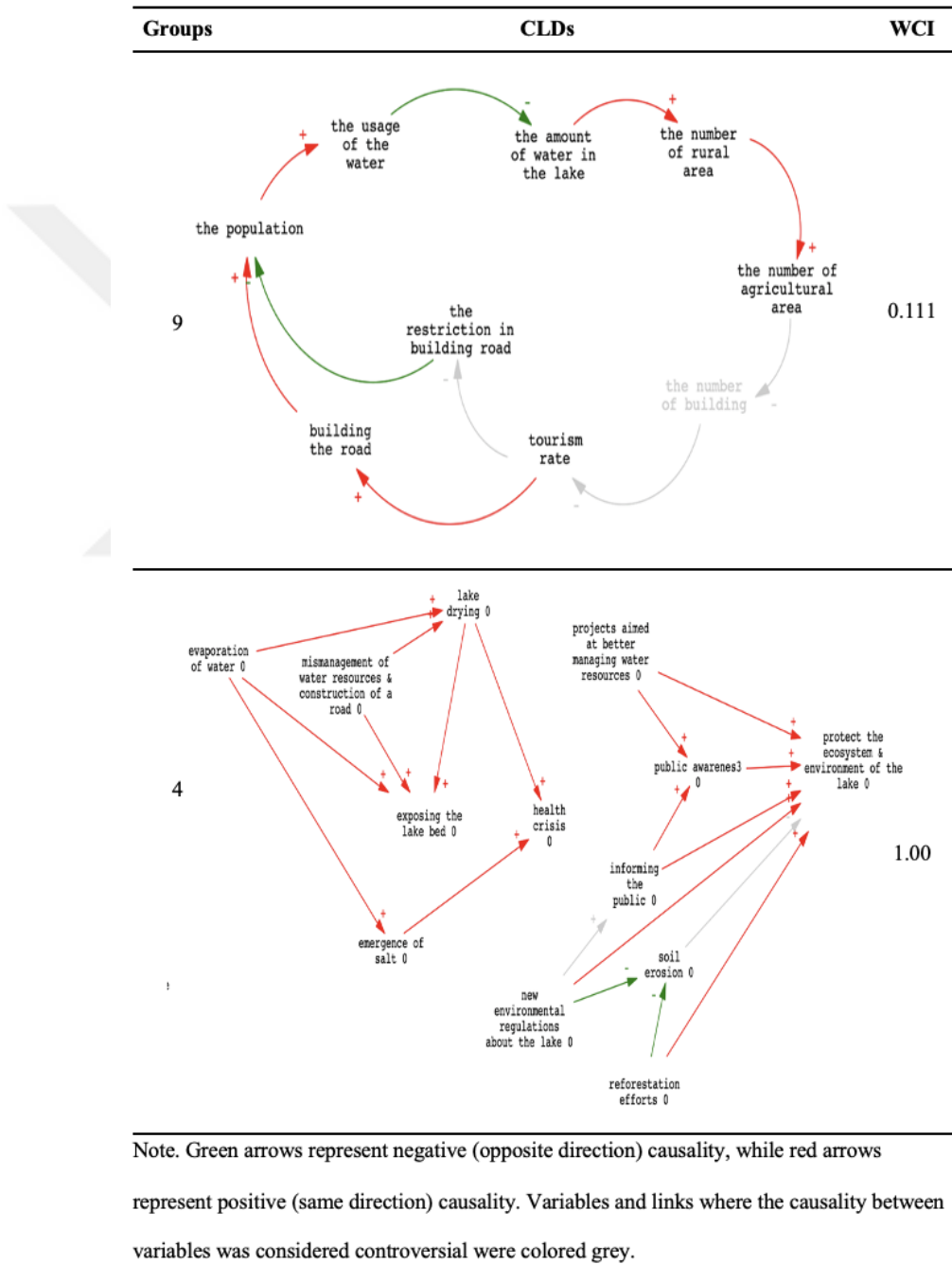


Figure 4.45. CLDs with the highest and lowest web-like causality (WCI) among the groups.

4.3.2. Feedback Loops

To analyze the feedback mechanism in causal loop diagrams, the number of feedback loops and feedback density values were determined.

As illustrated in Figure 4.46, no feedback loop could be identified in five groups (Group 4, Group 7, Group 9, Group 11, Group 17). Four groups (Group 1, Group 2, Group 12, and Group 15) exhibited two feedback loops. Five groups (Group 5, Group 6, Group 8, Group 10 and Group 16) exhibited three feedback loops. One group (Group 14) exhibited four feedback loops, while one group (Group 3) exhibited seven feedback loops, and one group (Group 13) exhibited six feedback loops.

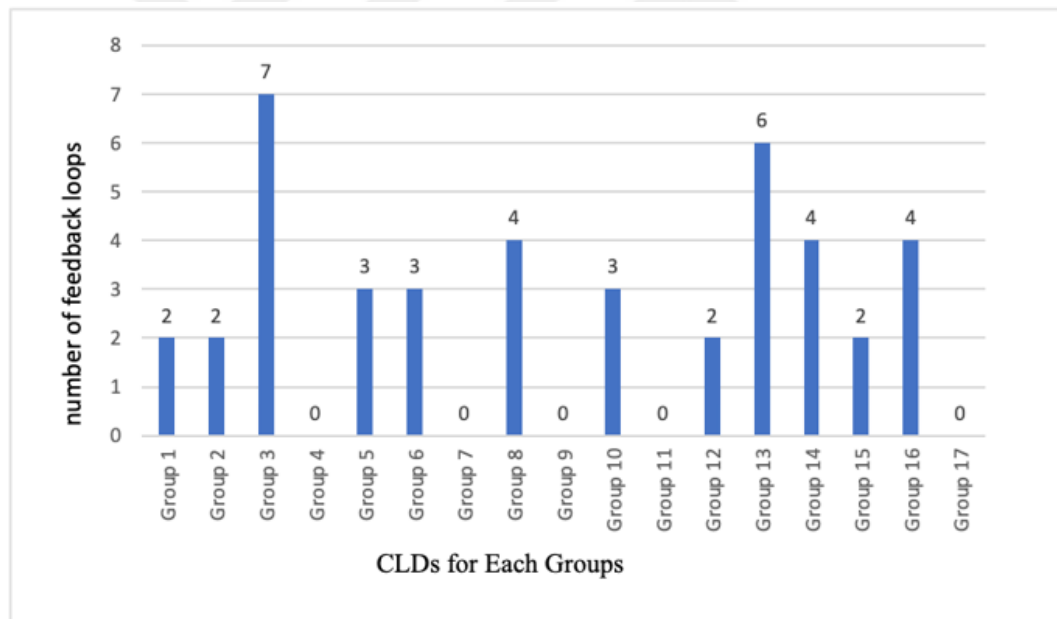


Figure 4.46. Number of feedback loops in CLDs for each group.

Another important measure, feedback density, was calculated as the ratio of variables (nodes) and links in the feedback loops to the total number of variables (nodes) and links. Therefore, the feedback density value can vary between 0.00 and 1.00. The distribution of feedback density values between the groups is given in Figure 4.46. The feedback density value for the five groups was 1.00, which is considered to be the maximum value for this measure. On the other hand, the feedback density value for five

groups is 0.00, which is considered as the minimum value for this measure. The mean value of feedback density for all groups was .51, indicating a moderate feedback density ($n = 17$, $SD = .415$) with a minimum value of 0.00 and a maximum value of 1.00.

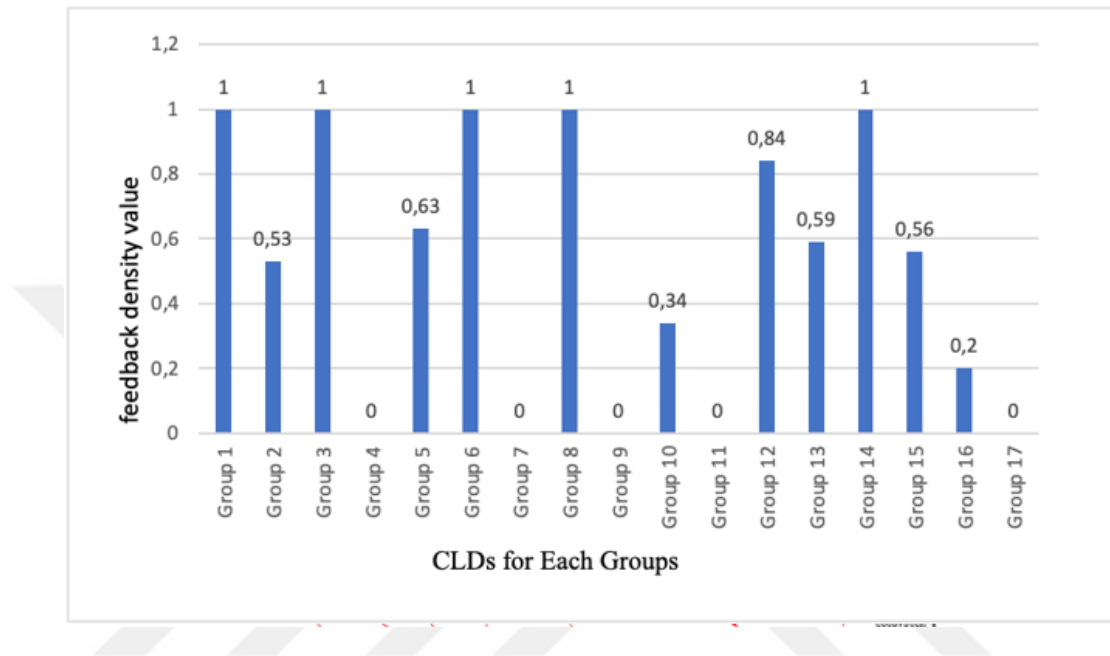
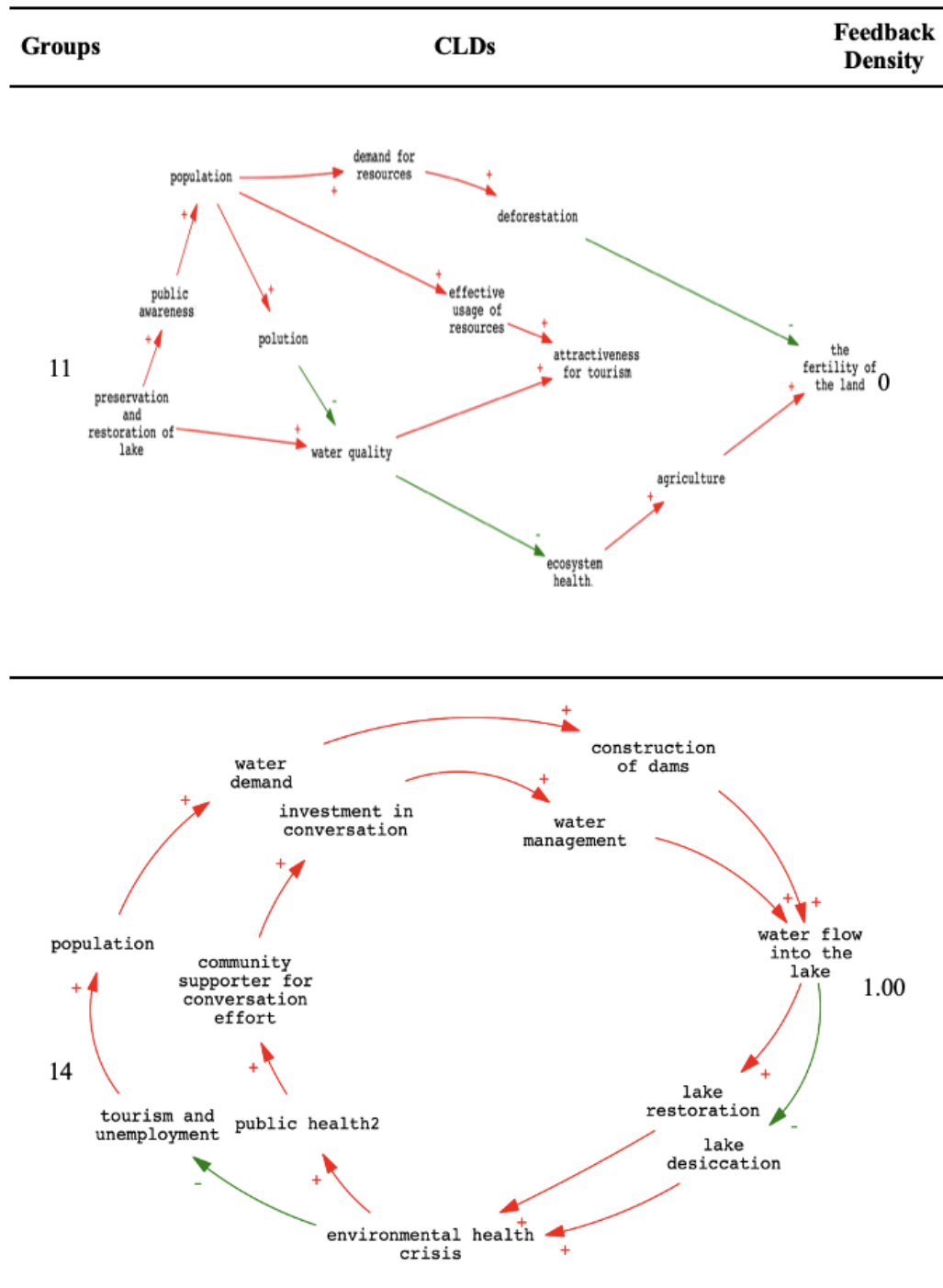


Figure 4.47. Feedback Density Values in CLDs for each group.

Figure 4.48 shows the causal loop diagrams with the highest and lowest feedback density values among the groups. Group 11 and Group 14 consisted of 12 variables and 14 links. Therefore, their link density values were the same. However, the structure of causal loop diagrams was different. Group 11 causal loop diagram had branched and a linear causality and no feedback loop. Therefore, the feedback density was found to be 0. On the other hand, group 14 causal loop diagrams had all variables in the feedback loops, therefore, the feedback density was found to be 1. It was an important observation to show how structures were different regarding feedback loops.



Note. Green arrows represent negative (opposite direction) causality, while red arrows represent positive (same direction) causality. Variables and links where the causality between variables was considered controversial were colored grey.

Figure 4.48. CLDs with the highest and lowest feedback density values among the groups.

4.3.3. Complexity

The complexity of the mental model derived from causal loop diagrams was analyzed in terms of cyclomatic complexity and causal complexity. Cyclomatic complexity was calculated using the formula $\text{Links} - \text{Nodes} + 2 \times \text{Connected Components}$. Figure 4.8 shows the distribution of cyclomatic complexity values for each group. The majority of the groups had cyclomatic complexity values below 10. Three groups had values above 10. For comparison, the cyclomatic complexity value of the expert causal loop diagram was also calculated and found to be 11. When the cyclomatic complexity exceeds 10, the testability of the system becomes a challenge. It was stated that a higher cyclomatic complexity score indicates a more complex system (McCabe, 1976).

In addition, as shown in Figure 4.49, twelve groups had a causal complexity value higher than their cyclomatic complexity. Causal complexity was calculated using the following formula: cyclomatic complexity multiplied by (1 plus feedback density). Therefore, the inclusion of feedback loops in the causal loop diagrams resulted in an increase in the causal complexity values. Twelve groups had at least one feedback loop in their causal loop diagrams. Only five groups had no feedback loops in their diagrams. Thus, it was shown that the inclusion of feedback loops contributes to an increase in system complexity.

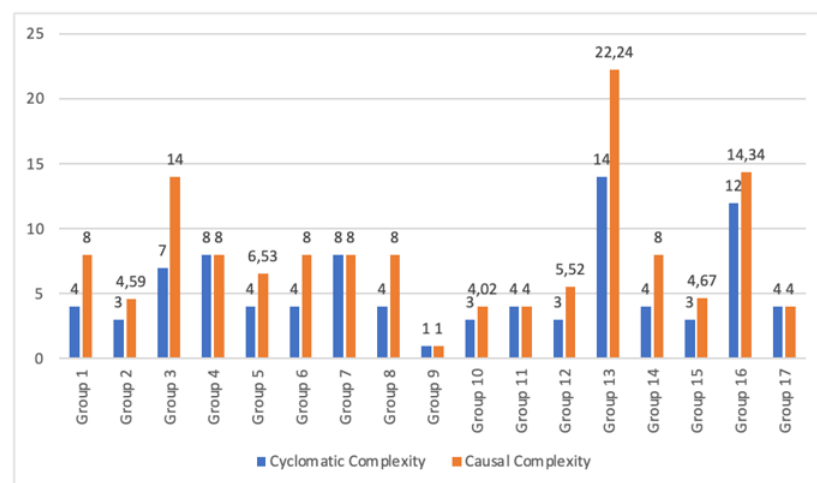
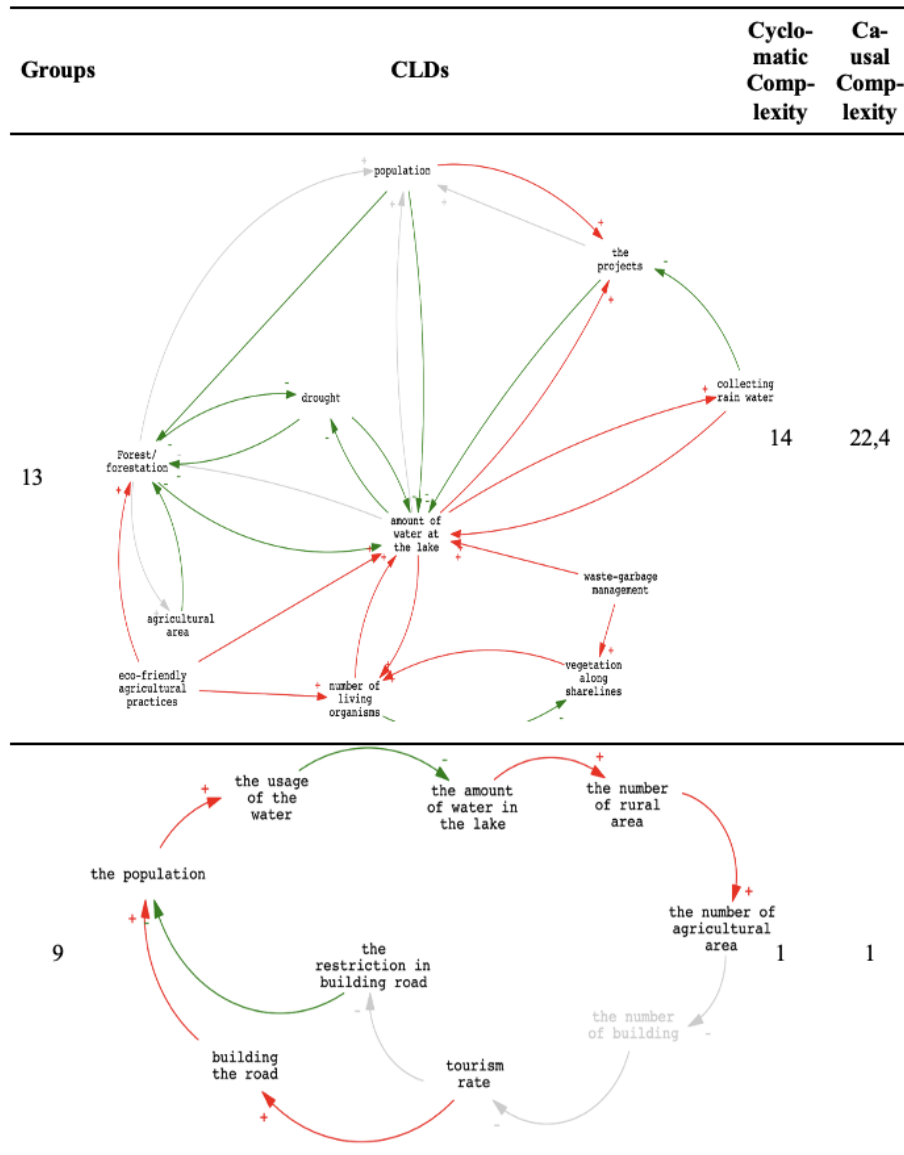


Figure 4.49. Distribution of cyclomatic complexity and causal complexity values for each group.

The mean value of cyclomatic complexity was found to be 5.29 (n=17, SD = 3.442) with a minimum value of 1.0 and a maximum value of 14.00. The mean value of causal complexity value was found to be 7.81 (n=17, SD= 5.039) with a minimum value of 1.0 and maximum value of 22.24. Figure 4.50 presents the causal loop diagrams with the highest and lowest cyclomatic complexity and causal complexity among the groups. Group 13 exhibits the highest cyclomatic complexity and causal complexity value among the other groups, while Group 9 demonstrates the lowest cyclomatic complexity and causal complexity value among the other groups.

As seen in Figure 4.50, Group 13 had a single connected component with 11 variables and 23 links. According to the formula, the cyclomatic complexity value was calculated as 14. To capture the complexity of systems in terms of feedback loops, causal complexity values were calculated. Causal complexity is calculated using the formula $\text{cyclomatic complexity} * (1 + \text{feedback density})$ and is related to cyclomatic complexity and feedback density. Since the causal complexity was increased by feedback loops, the causal complexity value of Group 13 was calculated to be 22.4.

On the other hand, Group 9 had one component with eight variables and seven links. According to the formula, the cyclomatic complexity value was calculated as 1.00, which was the lowest value among the groups. Similarly, the causal complexity value of Group 9 was calculated as 1 because Group 9 had no feedback loop, which means that the feedback density value was 0.00.



Note. Green arrows represent negative (opposite direction) causality, while red arrows represent positive (same direction) causality. Variables and links where the causality between variables was considered controversial were colored grey.

Figure 4.50. CLDs with the highest and lowest cyclomatic complexity and causal complexity among the groups.

4.4. Results of the Third Research Question

RQ3: To what extend do systems complexity of preservice teachers' written explanations and causal loop diagrams on climate change-based case scenarios differ?

Table 4.5 provided a comparison of mental models derived from written explanations and drawn CLDs in terms of the number of variables, number of links, number of feedback loops, link density, web-like causality index, feedback density, cyclomatic complexity, and causal complexity. It was found that pre-service teachers identified more variables by writing explanations ($M = 15.94$, $SD = 5.629$) than by drawing causal loop diagrams ($M = 12.71$, $SD = 3.177$). However, pre-service teachers identified more cause-effect relationships (links) by drawing causal loop diagrams ($M = 15.88$, $SD = 5.048$) than by writing explanations ($M = 14.29$, $SD = 5.241$).

The link density and WCI measures indicated the extent to which the model contains interconnected relationships and the extent to which these relationships can be linear or branched. The results demonstrated that the mental model reflected by drawing causal loops exhibits a higher link density ($M = 1.25$, $SD = .277$) than the mental model reflected by writing ($M = .90$, $SD = .14$). Similarly, the mental model reflected by drawing causal loops exhibits a higher web-like causality index ($M = .450$, $SD = .241$) than the mental model reflected by writing ($M = .230$, $SD = .127$). It was shown that pre-service teachers were able to better reflect their mental models by drawing causal loops in terms of interconnections. Feedback density indicates the fraction of elements in the feedback loops in the model relative to the whole model. The results demonstrated that the mental model reflected by drawing causal loops exhibits a higher feedback density ($M = .51$, $SD = .415$) than the mental model reflected by writing ($M = 0.00$, $SD = 0.00$).

Cyclomatic complexity and causal complexity indicate the structural complexity of a given system. The results demonstrated that the mental models reflected by drawing causal loops exhibited a higher cyclomatic complexity ($M = 5.29$, $SD = 3.442$) than those reflected by writing ($M = 3.18$, $SD = 1.185$). Similarly, mental models reflected by drawing causal loops exhibited a higher causal complexity ($M = 7.81$, $SD = 5.039$) than the mental models reflected by writing ($M = 3.18$, $SD = 1.185$). It was shown that preservice teachers were able to reflect more complex mental models by drawing causal loops.

Table 4.5. Comparison of mental models derived from written explanations and drawn CLDs.

<i>Criteria</i>	<i>Measures</i>	<i>Written Exp.</i>		<i>Drawn CLDs</i>		
		<i>Mean</i>	<i>Std. Dev.</i>	<i>Mean</i>	<i>Std. Dev.</i>	<i>n</i>
	Total Variable	15.94	5.629	12.71	3.177	17
	Total Cause – Effect (link)	14.29	5.241	15.88	5.048	17
	# of feedback loops	0.00	0.000	2.47	2.125	17
Interconnections	Link Density	0.90	0.14	1.25	.277	17
	Web-like Causality Index (WCI)	0.230	0.127	0.450	.241	17
Feedback	Feedback Density	0.00	0.000	0.51	.415	17
Complexity	Cyclomatic Complexity	3.18	1.185	5.29	3.442	17
	Causal Complexity	3.18	1.185	7.81	5.039	17

Figure 4.51 provides an overview of the comparison of mental models derived from written explanations and mental models derived from the causal loop across all measures. In addition, a detailed comparison between mental models derived from written explanations and mental models derived from the causal loop is shown in the colour table. Changes in numerical scores are shown in the table, with darker colours indicating higher scores and lighter colours indicating lower scores (Appendix H).

In order to find out whether there was a statistical difference between the pre-service teachers' written explanations and the causal loop diagrams on system complexity, the Wilcoxon test was used, which is a non-parametric test. The results were detailed in three subheadings: interconnection, feedback, and complexity

4.4.1. Interconnection

The mental models obtained from pre-service teachers' written explanations and causal loop diagrams were compared in terms of interconnection dimension. For this reason, the link density and web-like causality index measures of the models were analyzed.

As seen in Figure 4.51a, in 16 groups, the link density of mental models derived from causal loops were higher than mental models derived from written explanations. Only one group (Group 9), link density of mental models derived from causal loops was lower than mental models derived from written explanations.

- Is there a significant difference between the mental models derived from written explanations and mental models derived from causal loop diagrams in terms of link density?

To answer this question the Wilcoxon signed-rank test was used as a non-parametric test to compare, as the sample consisted of 17 groups and the number was less than 30. Table 4.6 shows the results of the Wilcoxon signed-rank test for link density. According to the results, there were 16 positive ranks, indicating higher values of link density for the drawn CLDs, and one negative rank, indicating a lower value for the drawn CLDs. There were no ties, meaning that the link density value for each condition was not the same. There was a statistically significant difference in the link density between mental models derived from written explanations and mental models derived from causal loop diagrams, $N = 17$, $z = 3.527$, $p = < 0.001$, with a large effect size, $r = 0.86$ (Cohen, 1992).

Table 4.6. Wilcoxon signed-rank test results for link density.

		n	z	p
Link density (drawn CLD) - Link density (text)	Negative Ranks	1 ^a	-3.527	<0.001
	Positive Ranks	16 ^b		
	Ties	0 ^c		
	Total	17		

a. Link density (drawn CLD) < Link density (text)

b. Link density (drawn CLD) > Link density (text)

c. Link density (drawn CLD) = Link density (text)

Figure 4.51b shows the comparison of mental models derived from written explanations and mental models derived from causal loop diagrams regarding web-like causality index. In 14 groups, the web-like causality index of mental models derived from causal loops was higher than that derived from written explanations. In 3 groups (Group 7, Group 8, and Group 9), the web-like causality index of mental models derived from causal loops was lower than mental models derived from written explanations.

- Is there a significant difference between the mental models derived from written explanations and mental models derived from causal loop diagrams in terms of web-like causality index?

To answer this question, the Wilcoxon signed-rank test was used as a non-parametric test to compare, as the sample consisted of 17 groups, and the number was less than 30. Table 4.7 shows the results of the Wilcoxon signed-rank test for the web-like complexity index. According to the results, there were 14 positive ranks, indicating higher values of web-like causality index for the drawn CLDs, and 3 negative ranks, indicating a lower value for the drawn CLDs. There were no ties, meaning that the web-like causality index for each condition was not the same. There was a statistically significant difference in the web-like causality index between mental models derived from written explanations and mental models derived from causal loop diagrams, $N=17$, $z= -2.911$, $p= 0.004$, with a large effect size, $r=0.70$ (Cohen, 1992).

Table 4.7. Wilcoxon signed-rank test results web-like causality index.

		n	z	p
Web-like Causality Index (drawn CLD) – Web-like Causality Index (text)	Negative Ranks	3 ^a	-2.911	0.004
	Positive Ranks	14 ^b		
	Ties	0 ^c		
	Total	17		
a. Web-like Causality Index (drawn CLD) < Web-like Causality Index (text) b. Web-like Causality Index (drawn CLD) > Web-like Causality Index (text) c. Web-like Causality Index (drawn CLD) = Web-like Causality Index (text)				

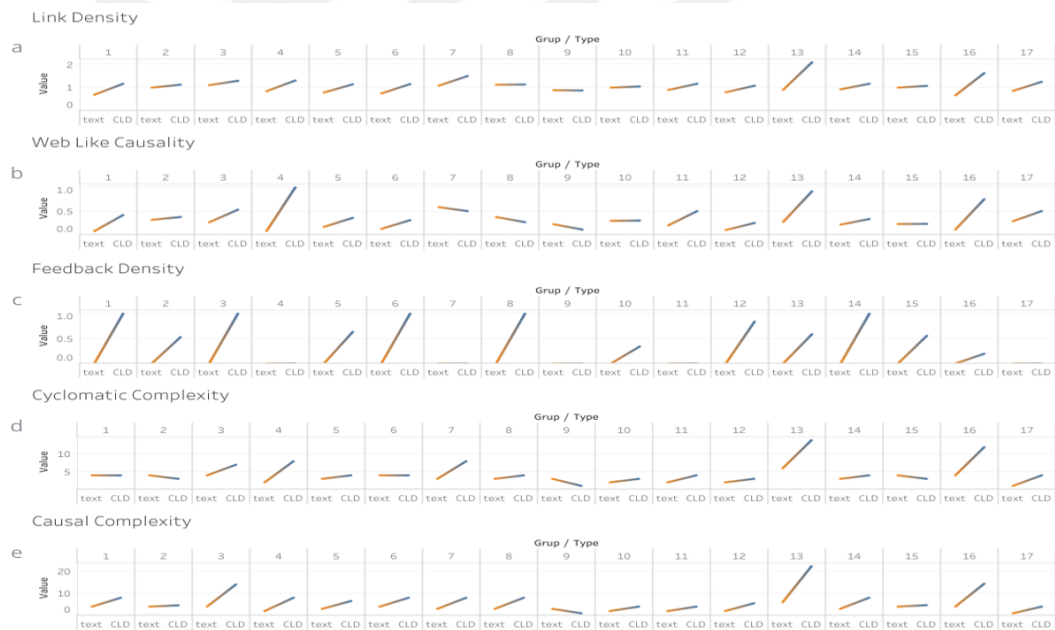


Figure 4.51. Comparison of measures of participants' mental models derived from written explanations (text) and drawn CLDs.

Text refers to mental models derived from written explanations. CLD refers to mental models derived from causal loop diagrams

4.4.2. Feedback

The mental models obtained from pre-service teachers' written explanations and causal loop diagrams were compared in terms of feedback dimension. For this reason, feedback density measure of the models was analyzed.

Figure 4.51c shows the comparison of mental models derived from written explanations and mental models derived from causal loop diagrams in terms of feedback density. In 12 groups, the feedback density of mental models derived from causal loops were higher than mental models derived from written explanations. In addition, 5 groups (Group 4, Group 7, Group 9, Group 11 and Group 17) have the same feedback density values in both.

- Is there a significant difference between the mental models derived from written explanations and mental models derived from causal loop diagrams in terms of feedback density?

To answer this question wilcoxon signed-rank test was used as a non-parametric test for comparison. Table 4.8 shows the results of the Wilcoxon signed-rank test for feedback density. According to the results, there were 12 positive ranks, which means 12 groups have a higher feedback density value for mental models by derived from causal loop diagrams. There were zero negative ranks, which means no groups have a higher feedback density value for mental models by derived written explanations.

There were five ties, which means where the feedback density values of mental models derived from causal loop diagrams and written explanations were the same. It was found that there was a statistically significant difference in the feedback density between mental models derived from written explanations and mental models derived from causal loop diagrams, $n = 17$, $z = -3.083$, $p = .002$, with a large effect size, $r = 0.75$ (Cohen, 1992).

Table 4.8. Wilcoxon signed-rank test results for feedback density.

		n	z	p
Feedback Density (drawn CLD) – Feedback Density (text)			-3.083	0.002
	Negative Ranks	0 ^a		
	Positive Ranks	12 ^b		
	Ties	5 ^c		
	Total	17		
a. Feedback Density (drawn CLD) < Feedback Density (text)				
b. Feedback Density (drawn CLD) > Feedback Density (text)				
c. Feedback Density (drawn CLD) = Feedback Density (text)				

4.4.3. Complexity

To compare the complexity of mental models derived from written explanations and mental models derived from causal loop diagrams, measures of cyclomatic complexity and causal complexity were calculated. Causal complexity is a measure that encompasses cyclomatic complexity and feedback density.

Figure 4.51d shows the comparison of mental models derived from written explanations and mental models derived from causal loop diagrams regarding cyclomatic complexity. In twelve groups, the cyclomatic complexity of mental models derived from causal loops was higher than mental models derived from written explanations. In three groups (Group 2, Group 9, and Group 15), the cyclomatic complexity of mental models derived from causal loops was lower than mental models derived from written explanations. In addition, two groups, Group 1 and Group 6, have the same cyclomatic complexity.

- Is there a significant difference between the mental models derived from written explanations and mental models derived from causal loop diagrams in terms of cyclomatic complexity?

To answer this question, the Wilcoxon signed-rank test was used as a non-parametric test for comparison. Table 4.9 shows the results of the Wilcoxon signed-rank

test for cyclomatic complexity. According to the results, there were 12 positive ranks, which means 12 groups have a higher cyclomatic complexity value for mental models derived from causal loop diagrams. There were three negative ranks, which means three groups have a higher cyclomatic complexity value for mental models by derived written explanations.

There were five ties, which means that the cyclomatic complexity values of mental models derived from causal loop diagrams and written explanations were the same. It was found that there was a statistically significant difference in the cyclomatic complexity between mental models derived from written explanations and mental models derived from causal loop diagrams, $n = 17$, $z = -2.500$, $p = .012$, with a large effect size, $r = 0.60$ (Cohen, 1992).

Table 4.9. Wilcoxon signed-rank test results cyclomatic complexity.

		n	z	p
Cyclomatic Complexity (drawn CLD) – Cyclomatic Complexity (text)	Negative Ranks	3 ^a	-2.500	0.012
	Positive Ranks	12 ^b		
	Ties	2 ^c		
	Total	17		
a. Cyclomatic Complexity (drawn CLD) < Cyclomatic Complexity (text)				
b. Cyclomatic Complexity (drawn CLD) > Cyclomatic Complexity (text)				
c. Cyclomatic Complexity (drawn CLD) = Cyclomatic Complexity (text)				

Figure 4.51e indicates the comparison of mental models derived from written explanations and mental models derived from causal loop diagrams regarding causal complexity. In 16 groups, the causal complexity of mental models derived from causal loops was higher than mental models derived from written explanations. In one group (Group 9), the causal complexity of mental models derived from causal loops was lower than mental models derived from written explanations.

- Is there a significant difference between the mental models derived from written explanations and mental models derived from causal loop diagrams in terms of causal complexity?

To answer this question the Wilcoxon signed-rank test was used as a non-parametric test for comparison. Table 4.10 shows the results of the Wilcoxon signed-rank test for causal complexity. According to the results, there were 16 positive ranks, which means 16 groups have a higher causal complexity value for mental models derived from causal loop diagrams. There was one negative rank, which means one group has a higher causal complexity value for mental models by derived written explanations.

There were 0 ties, which means that the causal complexity values of mental models derived from causal loop diagrams and written explanations were the same. It was found that there was a statistically significant difference in the causal complexity between mental models derived from written explanations and mental models derived from causal loop diagrams, $n = 17$, $z = -3.459$, $p = < 0.001$, with a large effect size, $r = 0.84$ (Cohen, 1992).

Table 4.10. Wilcoxon signed-rank test results for causal complexity.

		n	z	p
Causal Complexity (drawn CLD) – Causal Complexity (text)	Negative Ranks	1 ^a	-3.459	<0.001
	Positive Ranks	16 ^b		
	Ties	0 ^c		
	Total	17		
a. Causal Complexity (drawn CLD) < Causal Complexity (text)				
b. Causal Complexity (drawn CLD) > Causal Complexity (text)				
c. Causal Complexity (drawn CLD) = Causal Complexity (text)				

4.5. Summary of Results of Research Questions

To answer the first research question, the researcher transformed pre-service teachers' written explanations into causal loop diagrams to visualize the representations of mental models. The pre-service teachers' mental model representations based on their written explanations were examined regarding interconnection, feedback, and complexity.

- The pre-service teachers' mental model representations based on their written explanations had linear and branching structures, but no feedback loop existed.
- In terms of complexity, cyclomatic complexity showed a limited value, but causal complexity reached the same value as cyclomatic complexity due to the lack of feedback loops in the representations.
- The pre-service teachers' mental model representations based on their written explanations have limited complexity in that they ignored feedback loops and contained separate structures.

To answer the second research question, the researcher analyzed the causal loop diagrams drawn by the pre-service teachers. The pre-service teachers' causal loop diagrams were examined regarding interconnection, feedback, and complexity.

- Most of the pre-service teachers' causal loop diagrams were non-linear, branched, and had feedback loops.
- When the pre-service teachers reflected their mental models with causal loop diagrams, most of them were able to include feedback loops; as a result, the feedback density of the pre-service teachers' causal loop diagrams was close to moderate.
- Cyclomatic and causal complexity were found to be different. Causal complexity includes cyclomatic complexity and rewards the presence of feedback loops. Therefore, the complexity of pre-service teachers' causal loop diagrams increased due to the presence of feedback loops.

To answer the third research question, the researcher compared pre-service teachers' mental model representations based on written explanations and causal loop diagrams regarding interconnection, feedback, and complexity.

- When pre-service teachers drew causal loop diagrams to reflect their mental models, they formed a more interconnected structure than when writing an explanation.
- When pre-service teachers drew causal loop diagrams to reflect their mental models, they included feedback loops than when writing an explanation.
- When pre-service teachers drew causal loop diagrams to reflect their mental models, they reflected more complex mental models than when writing an explanation.

5. DISCUSSION

5.1. Discussion of First Research Question

This section presents the discussion under six headings; the first three headings discuss the research questions respectively, and the remaining headings present implications, limitations, and suggestions for future research.

People have mental models based on their experiences and observations. However, mental models can limit decisions about complex problems (Forrester, 2016). There are studies on mental models, and in this direction, attempts have been made, such as transforming interviews and open-ended questions into causal loop diagrams (Haque *et al.*, 2023; Kim and Andersen, 2012; Owen *et al.*, 2018). Transforming qualitative data into causal loop diagrams is an important endeavor and enables the visualization of mental models. Also, open-ended questions on real-world scenarios can be used to measure the systems thinking abilities of individuals (Davis *et al.*, 2020; Grohs *et al.*, 2018). Therefore, the current study provides insight to examine pre-service teachers' responses related to a climate change-based scenario and transforms the written data into causal loop diagrams.

The greater the number of variables in a system and the greater the links between these variables, the more complex the system becomes. However, to have dynamic complexity, interconnection of variables, feedback loops, non-linearity, and delay should also be considered (Stermann, 2000). Results showed that pre-service teachers could identify and relate the variables, but their mental models mostly linear, branched structures and no feedback. The lack of connection between separate structures and feedback mechanisms may mean their mental models lack dynamic complexity. Similarly, according to Haque *et al.* (2023), the mental models of engineering graduate students have a linear or branched structure, and very few contain feedback loops. These findings are consistent with the results of the current study. In contrast to Haque *et al.*'s

(2023) study, the current study shows that no feedback loops in the mental model representations of pre-service teachers. Similarly, in the study of Sweeney and Sterman (2007), teachers had difficulty in describing feedback processes where feedback is provided through scenarios about economic and ecological concepts. The results of the current study visualised pre-service teachers' explanations of the complex problem of climate change and showed that their mental models had a simple and linear structure and were limited in terms of feedback mechanisms, which are important for systems thinking. This implies that pre-service teachers have difficulty recognising the interconnections between climate components and understanding them as a complex system. It is recommended that teacher preparation programs need to include practical exercises that go beyond simple and linear causal thinking and activate their thinking by paying attention to feedback mechanisms, thus allowing a guided transition to a complex mental model structure.

In a study conducted with highly educated individuals, participants' systems thinking skill was limited (Cronin *et al.*, 2009). The literature emphasizes that systems thinking is a competency beyond mathematics or science background (Sweeney and Sterman, 2000). The participants of this study were mainly pre-service teachers studying in the mathematics and science departments of one of the leading universities in the country. Consistent with the literature, the results showed that pre-service teachers have limited understanding and mental models without feedback mechanisms (Lee *et al.*, 2019; Palmberg *et al.*, 2017).

The limited capacity for systems thinking may be due to the limited rationality of complex problems. The scenario used in the current study includes different dimensions of climate change interactions as a complex problem. Climate change is an unpredictable and uncertain system problem with insufficient wait-and-see policies. In other words, it is difficult for individuals to understand the dynamic nature of climate change and experience its future behavior (Sweeney and Sterman, 2000). In contrast, it was shown the opposite, the limited ability to engage in systems thinking in familiar contexts such as the bathtub or the bank account raises the question of whether this

is due to more than the complex nature of the problem (Sterman and Sweeney, 2002; Sweeney and Sterman, 2000) At this point, the current study argues that the complex nature of the context is noteworthy, but a different perspective is needed.

5.2. Discussion of Second Research Question

Studies in the literature investigated systems thinking skills using model-building techniques such as causal maps, concept maps, and causal loop diagrams (e.g., Cox *et al.*, 2019; Gray *et al.*, 2019; Leung *et al.*, 2024; Tripto *et al.*, 2013). According to Cox *et al.* (2019), one of the skills of a systems thinker is to construct causal loop diagrams from given information. Similarly, Leung *et al.* (2024) state that a systems thinker can construct and revise causal loops from given information and use them to solve problems. Schultz *et al.* (2022) indicate that having students draw maps can improve their systems thinking skills by enabling them to recognize the components and relationships within systems. According to Schultz *et al.* (2022), constructing system maps can be a helpful practice tool and drawing system maps allows students to reflect on their systems thinking skills. Consistent with the existing literature, the present study supports the idea that constructing causal loop diagrams is an indicator of being good at systems thinking. In this context, in the present study, participants drew causal loop diagrams to address the problem in the given climate change scenario, the interactions between the components of the problem, and the proposed solution to the problem. Thus, the present study implies that causal loop diagrams can be used as a tool to visualize individuals' mental models and gain insight into their understanding of systems.

Constructing causal loop diagrams starts with defining the problem, then identifying its boundaries and components and adapting it to a specific context. The problem is likely to be invisible and has hidden dimensions, so it is important that this process is carried out as a group and can be addressed through group discussions (Haraldsson, 2004). Similarly, Leung *et al.* (2024) stated that constructing causal loop diagrams collaboratively enables participants to better reflect their mental models by exchanging

ideas and recognizing more interactions and variables within the system related to a complex problem. In the current study, pre-service teachers constructed causal loop diagrams as a group based on a given scenario related to climate change. This study supports the idea that collaboration can contribute to the reflection of more complex mental models. It may therefore mean that discussion and interaction between individuals can be important in processes that require more active participation, such as model building. Further research is recommended in this regard.

The present study has emphasized the potential of causal loop diagrams to examine complex mental models. Causal loop diagrams are a specific tool that better shows cause-effect relationships and feedback (Lane, 2008; Schaffernicht, 2007). Creating a causal loop diagram is a process that requires critical thinking because it involves evaluating how relationships between concepts are realized. Using causal loop diagrams provides a pathway from thinking to action by helping move from linear to closed loop thinking (Cavana and Mares, 2004). In line with the literature, the current study shows that most of the participants included feedback loops in their causal loop diagrams, and their causal loop diagrams moved away from a linear structure. Causal loop diagrams provide a step in thinking about feedback, and including feedback increases causal complexity (Naugle *et al.*, 2023).

Also, results show that some pre-service teachers' drawings resembled a closed loop; in reality, they were far from being a closed loop and indicated a branched structure. Disorganized drawings or a tendency to over-link one variable can be observed. Moreover, in some of them, the connections between variables may not show a causal relationship (Szozda *et al.*, 2023). This means that analyzing only the quantitative aspects of mental models, such as the number of variables, number of links, etc., may provide limited insights.

5.3. Discussion of the Third Research Question

In the current study, pre-service teachers responded to questions about a complex scenario in the context of climate change by expressing them in written form, and these answers were transformed into causal loop diagrams by the researchers. At the same time, pre-service teachers answered these questions by drawing causal loops. The third research question of this study examined whether there was a difference in complexity between the mental model representations created by written or drawn mental model representations as causal loop diagrams.

The results showed that the pre-service teachers' drawn causal loop diagrams contained more interrelations, had more feedback mechanisms, and indicated a more complex structure than the mental model representations obtained from written explanations. The results aligned with the study of Schmidt *et al.* (2024), which showed that concept mapping is better for systems understanding than verbal explanations. For this study, the concept maps constructed by participants to assess their understanding of the system were compared with the concept maps constructed from their verbal explanations. This study showed that the concept maps created by the participants contained more functional relations than their verbal explanations (Schmidt *et al.*, 2024). Similarly, Nesbit and Adesope (2006) found that concept mapping is more effective for learning than creating text. Concept mapping requires many decisions to be made, such as which concepts to select, how to relate them to each other, and how to position them as concepts (nodes) and connections (links). It requires more elaboration than writing an explanation (Schroeder *et al.*, 2018). Therefore, the current study suggested that learners need to be encouraged to create their own models to increase their decision skills. In particular, this study implies that modeling complex scenarios such as climate change can enable people to become aware of the multiple effects of their own actions, be active in the process, and thus develop complex mental models. Interactions to initiate mental model development should be integrated into teacher education programs by encouraging systems thinking practices and facilitating them with system dynamics tools.

According to the results of the present study, it is seen that the number of concepts that the participants identified by writing are higher than the concepts they formed by drawing. However, when participants drew causal loop diagrams, they drew more relationships. Similarly, Hung (2008) reported that some students had difficulties in identifying crucial variables when creating causal loops even though they thought they were good at conceptualization, and it is seen that as the level of system thinking increases, the possibility of having difficulty in conceptualization increases.

The present study compared the participants' mental models with different measures in three dimensions; interconnections (link density and web-like causality index), feedback (feedback density), complexity (cyclomatic and causal complexity). Across all measures, most participants show higher performance when constructing causal loop diagrams rather than an explanation. The result of the present study shows that mental models derived from written explanations are mostly linear and branched. When participants drew causal loop diagrams, their mental models improved in terms of interconnections. The ratio of links to nodes (link density) increased, and they had more branched structures (web-like causality index). These findings are consistent with the results of Jeong and Lee's (2012) study, in which participants had higher link-node ratios when attempting to construct causal maps. Also, in Plate's (2010) study, causal maps were used to assess systems thinking before and after systems thinking intervention. The causal maps in the post-test were found to have more branched structures which means increase on the web-like causality index.

The result of the present study shows that mental models derived from written explanations did not include feedback loops. When participants drew causal loop diagrams, they were able to demonstrate their mental models more effectively in terms of feedback. The present study supported that allowing participants to construct causal loop diagrams can improve their understanding of feedback mechanisms and allow them to think about how loops affect components (Roychoudhury *et al.*, 2017). In addition, it was found that the structures in the causal maps of participants who received systems thinking training shifted from linear to non-linear (Plate, 2010).

Causal complexity, a broader measure that includes cyclomatic complexity and feedback density, provides insight into the system complexity of structures (Naugle *et al.*, 2023). According to the findings of the current study, participants included more non-linear structures and feedback loops when drawing causal loop diagrams. The inclusion of feedback loops increased the causal complexity of mental models. Therefore, it was found that the mental models derived from the causal loop diagrams drawn by the participants have a more complex structure than those derived from the written explanations.

System dynamics tools could be effective for sustainability learning, as they allow for holistic thinking while considering different parts of the system and their interactions (Brychkov *et al.*, 2024). According to Forrester (2016), taking an active role in system dynamics modeling is necessary, rather than practicing from a prepared system model, which helps individuals gain insights into understanding complex systems. In line with the literature, the current study supported the importance of the participants' active engagement in modeling to visualize mental models for a real-world scenario related to climate change.

According to the results of this study, the limited mental models of most of the pre-service teachers shifted into a mental model with more complex elements by drawing causal loops. Thus, it gives the idea that mental models can be improved with the active participation of individuals in modeling. Similarly, the literature suggested that mental models can be developed with well-prepared activities or scaffolded questions (Ben Zvi Assaraf, and Orion, 2005; Leung *et al.*, 2024). Also, it was pointed out that not every individual may develop at the same level (York *et al.*, 2019). Therefore, it is necessary to investigate further how individual differences such as academic or demographic differences impact modeling practices.

In this study, participants were presented with a scenario in which they were first asked to answer in writing and then to create causal loop diagrams. At this stage, the order in which the questions were answered may have affected the participants'

ability to answer, and this effect may have been mutually reinforcing. Further research is needed to establish whether the order in which participants answered the questions had any effect. To examine the effect, participants could be asked to answer this study again in reverse order. In addition, a comparative study could provide further evidence on how the expression method affects the ability to demonstrate mental models. In this study, for the questions of given scenario, one group would be asked to draw causal loop diagrams, and the other group would be asked to write an explanation.

5.4. Implications

The current study provided evidence by analyzing pre-service teachers' mental models of complex problems with different methods. Considering the limited number of studies conducted with pre-service teachers (e.g., Ceyhan *et al.*, 2024; Lee *et al.*, 2019; Tolppanen, and Kärkkäinen, 2021) the present study will contribute to systems thinking in the education field. First of all, by visualizing the components and interactions of a complex problem based on climate change with causal loop diagrams, pre-service teachers' perspective on this complex problem was revealed. Pre-service teachers' mental models based on written explanations were found to be quite limited. In addition, pre-service teachers were active in the modeling process and reflected their mental models by creating causal loop diagrams.

When pre-service teachers draw causal loop diagrams, their mental models contain more complex aspects. This result suggests that pre-service teachers' mental models can be improved through participation in active modeling sessions. The inclusion of system dynamics tools, especially when addressing complex system problems such as climate, ecosystem, and sustainability, suggests that practices to gain systems thinking competence in teacher education programs should be followed. This study underlines that raising the systems thinkers of the future can be realized by making today's teachers competent in systems thinking.

5.5. Limitations

This study has some limitations. The first limitation is related to generalizability. The participants of this study were selected using the purposive sampling method. In other words, they were selected according to a specific criterion, and they are pre-service teachers attending the climate change education course in the spring semester of 2024 at a state university. Therefore, it does not represent the whole number of pre-service teachers studying at universities in the country.

The second limitation is related to the nature of qualitative research. The Lake Urmia vignette, consisting of a scenario and two open-ended questions, was used as a data collection tool in this study. Participants responded to each question by writing explanations and drawing causal loops. Coding the written responses into causal loop diagrams is an intensive process. Therefore, it may be limited, especially when applied to large samples. In addition, even if a rubric developed by Kim and Andersen (2012) followed and an expert in systems thinking was consulted on several meetings, the selection of causal statements from the written responses and their transformation into names and arrows can be open to interpretation, especially since it is based on the explicit or implicit presence of some statements.

A possible limitation may be the effect of group dynamics. In this study, participants worked in groups. While working as a group fosters the exchange of ideas, this dynamic can vary. While some pre-service teachers may have expressed themselves better by writing, others may have done the same by drawing. This difference may have limited the dynamism within the group.

5.6. Recommendations for Future Research

This study was conducted with senior pre-service teachers taking the climate education course, and the mental models of pre-service teachers in the context of climate change were visualized and examined in terms of interconnections, feedback mecha-

nisms, and complexity. In this study, the written data obtained from the participants were transformed into causal loop diagrams and compared with those drawn by the participants. Drawing causal loop diagrams can be considered as the process before computer modeling. The following study can be conducted by having the participants use system dynamics modeling software such as Vensim, etc., in a computer environment. Other system dynamics tools (e.g., stock and flow diagrams) could also be used to teach different systems thinking skills (e.g., stock and flow thinking). Furthermore, this study could be extended to include first-year, sophomores, and juniors and compare the differences between levels.

This study provided valuable insights by collecting data from pre-service teachers at a specific time. Therefore, data can be collected at different times to understand better how pre-service teachers' mental models develop over time. In addition, when creating causal loop diagrams, repeated sessions can be conducted to allow participants to review their work. Also, support can be provided through scaffolding questions during the process. Furthermore, the data collection process can be videotaped. Thus, the group discussions and the steps they take while creating the diagrams can give more insight into their mental models. In addition, individual interviews can be conducted with the participants to assess their experiences of using causal loop diagrams. Thus, a detailed analysis of the experience and process of using causal loop diagrams can be carried out.

Future research could compare the responses of experts and novices in systems thinking. The expert map created in this study can be compared to the researcher's transformed representation of the same expert's written responses in terms of the system complexity. The same expert map can also be used to examine the extent to which participants approximated the expert map. Including different experts and novices from system thinking can increase the number of participants and improve the study.

REFERENCE

- Aminpour, P., S.A. Gray, M.W. Beck, K.L. Furman, I. Tsakiri, R.K. Gittman, J. Grabowski, J.F. Helgeson, L. Josephs, M. Ruth and S.B. Scyphers, 2022, “Urbanized Knowledge Syndrome-Erosion of Diversity and Systems Thinking in Urbanites’ Mental Models”, *npj Urban Sustainability*, Vol. 2, No. 1, pp. 11-20.
- Arnold, R.D. and J.P. Wade, 2015, “A Definition of Systems Thinking: A Systems Approach”, *Procedia Computer Science*, Vol. 44, No. 1, pp. 669-678.
- Arnold, R.D. and J.P. Wade, 2017, “A Complete Set of Systems Thinking Skills”, *Insight*, Vol. 20, No. 3, pp. 9-17.
- Ateskan, A. and J.F. Lane, 2018, “Assessing Teachers’ Systems Thinking Skills During A Professional Development Program in Turkey”, *Journal of Cleaner Production*, Vol. 172, No. 1, pp. 4348-4356.
- Bar-Yam, Y., 2002, *General Features of Complex Systems*, *Encyclopedia of Life Support Systems*, United Nations Educational, Scientific and Cultural Organization (UNESCO), Encyclopedia of Life Support Systems (EOLSS) Publishers, Oxford.
- Barbrook-Johnson, P. and Penn, A. S. (2022). *Causal loop diagrams. In Systems Mapping: How to build and use causal models of systems*. Springer International Publishing.
- Ben Zvi Assaraf, O. and N. Orion, 2005, “Development of System Thinking Skills in the Context of Earth System Education”, *Journal of Research in Science Teaching*, Vol. 42, No. 5, pp. 518-560.
- Ben Zvi Assaraf, O. and N. Orion, 2010, “System Thinking Skills at the Elementary

- School Level”, *Journal of Research in Science Teaching*, Vol. 47, No. 5, pp. 540-563.
- Beach, R., 2023, “Addressing the Challenges of Preparing Teachers to Teach About the Climate Crisis”, *The Teacher Educator*, Vol. 58, No. 4, pp. 507-522.
- Bhattacharya, D., K. Carroll Steward, and C.T. Forbes, 2021, “Empirical Research on K-16 Climate Education: A Systematic Review of the Literature”, *Journal of Geoscience Education*, Vol. 69, No. 3, pp. 223-247.
- Bielik, T., I. Delen, M. Krell, and O.B.Z. Assaraf, 2023, “Characterising the Literature on the Teaching and Learning of System Thinking and Complexity in STEM Education: A Bibliometric Analysis and Research Synthesis”, *Journal for STEM Education Research*, Vol. 1, No. 1, pp. 1-33.
- Boersma, K., A.J. Waarlo, and K. Klaassen, 2011, “The Feasibility of Systems Thinking in Biology Education”, *Journal of Biological Education*, Vol. 45, No. 4, pp. 190-197.
- Brychkov, D., P.C. McKeown, C. Domegan, C. Spillane, and G. Brychkova, 2024, “Connect the Circle Systems Thinking Tool for Postgraduate Sustainability Education: Case Study”, *International Journal of Sustainability in Higher Education*, Vol.25, No. 9, pp. 437-454.
- Capelo, C. and J.F. Dias, 2009, “A Feedback Learning and Mental Models Perspective on Strategic Decision Making”, *Educational Technology Research and Development*, Vol. 57, No. 1, pp. 629-644.
- Cavana, R.Y. and E.D. Mares, 2004, “Integrating Critical Thinking and Systems Thinking: From Premises to Causal Loops”, *System Dynamics Review: The Journal of the System Dynamics Society*, Vol. 20, No. 3, pp. 223-235.
- Ceyhan, G.D., U.S. Budak, and B. Karga, 2024, “Assessing the Pre-Service Science and

- Mathematics Teachers' Systems Thinking Skills through Case Scenarios", *Necatibey Faculty of Education Electronic Journal of Science and Mathematics Education*, Vol. 18, No. 2, pp. 375-403.
- Cox, M., J. Elen, and A. Steegen, 2019, "The use of Causal Diagrams to Foster Systems Thinking in Geography Education: Results of an Intervention Study", *Journal of Geography*, Vol. 118, No. 6, pp. 238-251.
- Cox, M., A. Steegen, and J. Elen, 2018, "Using Causal Diagrams to Foster Systems Thinking in Geography Education", *International Journal of Designs for Learning*, Vol. 9, No. 1, pp. 34-48.
- Cronin, M.A., C. Gonzalez, and J.D. Sterman, 2009, "Why Don't Well-Educated Adults Understand Accumulation? A Challenge to Researchers, Educators and Citizens", *Organizational Behavior and Human decision Processes*, Vol. 108, No. 1, pp. 116-130.
- Davis, K., N. Ghaffarzadegan, J. Grohs, D. Grote, N. Hosseinichimeh, D. Knight Mahmoudi and K. Triantis, 2020, "The Lake Urmia vignette: A Tool to Assess Understanding of Complexity in Socio-Environmental Systems", *System Dynamics Review*, Vol. 36, No. 2, pp. 191-222.
- Davis, A.C. and M.L. Stroink, 2015, "The Relationship Between Systems Thinking and the New Ecological Paradigm", *Systems Research and Behavioral Science*, Vol. 33, No. 4, pp. 575-586.
- Dawson, V., 2012, "Science Teachers' Perspectives about Climate Change", *Teaching Science: The Journal of the Australian Science Teachers Association*, Vol. 58, No. 1, pp. 3-15.
- Delaney, S., J.P. Ferguson, and M. Schultz, 2021, "Exploring Opportunities to Incorporate Systems Thinking into Science Education", *Journal of Science Education*, Vol. 53, No. 1, pp. 1-15.

rate Systems Thinking into Secondary and Tertiary Chemistry Education Through Practitioner Perspectives”, *International Journal of Science Education*, Vol. 43, No. 16, pp. 2618-2639.

Demssie, Y.N., H.J. Biemans, R. Wesselink, and M. Mulder, 2023, “Fostering Students’ Systems Thinking Competence for Sustainability by Using Multiple Real-World Learning Approaches”, *Environmental Education Research*, Vol. 29, No. 2, pp. 261-286.

Doganca Kucuk, Z. and A.K. Saysel, 2018, “Developing Seventh Grade Students’ Understanding of Complex Environmental Problems with Systems Tools and Representations: A Quasi-Experimental Study”, *Research in Science Education*, Vol. 48, No. 1, pp. 491-514.

Dorani, K., A. Mortazavi, A. Dehdarian, H. Mahmoudi, M. Khandan, and A.N. Mashayekhi, 2015, “Developing Question Sets to Assess Systems Thinking Skills”, *In Proceedings of the 33rd International Conference of the System Dynamics Society*, Cambridge, Massachusetts.

Dori, D., H. Sillitto, R.M. Griego, D. McKinney, E.P. Arnold, P. Godfrey, J. Martin and D. Krob, 2019, “System Definition, System Worldviews and Systemness Characteristics”, *The Institute of Electrical and Electronics Engineers Systems Journal*, Vol. 14, No. 2, pp. 1538-1548.

Dugan, K.E., E.A. Mosyjowski, S.R. Daly, and L.R. Lattuca, 2022, “Systems Thinking Assessments in Engineering: A Systematic Literature Review”, *Systems Research and Behavioral Science*, Vol. 39, No. 4, pp. 840-866.

Eberlein, R.L. and D.W. Peterson, 1992, “Understanding Models with Vensim”, *European Journal of Operational Research*, Vol. 59, No. 1, pp. 216-219.

- Eilam, B. 2012, "System Thinking and Feeding Relations: Learning with a Live Ecosystem Model", *Instructional Science*, Vol. 40, No. 1, pp. 213-239.
- Evagorou, M., K. Korfiatis, C. Nicolaou, and C. Constantinou, 2009, "An Investigation of the Potential of Interactive Simulations for Developing System Thinking Skills in Elementary School: A Case Study with Fifth-Graders and Sixth-Graders", *International Journal of Science Education*, Vol. 31, No. 5, pp. 655-674.
- Fanta, D., J. Braeutigam, and W. Riess, 2020, "Fostering Systems Thinking in Student Teachers of Biology and Geography-An Intervention Study", *Journal of Biological Education*, Vol. 54, No. 2, pp. 1-19.
- Feriver, Ş., 2022, "Pre-Schoolers as Systems Thinkers: Testing the Water", *Environmental Education Research*, Vol. 28, No. 3, pp. 430-456.
- Forrester, J.W., 1971, "Counterintuitive Behavior of Social Systems". *Theory and decision*, Vol. 2, No. 2, pp. 109-140.
- Forrester, J.W., 1994, "System Dynamics, Systems Thinking and Soft Or", *System Dynamics Review*, Vol. 10, No. 2-3, pp. 245-256.
- Forrester, J.W., 2016, "Learning Through System Dynamics as Preparation for the 21st Century", *System Dynamics Review*, Vol. 32, No. 3-4, pp. 187-203.
- Gilissen, M.G., M.C.P. Knippels, and W.R. van Joolingen, 2020, "Bringing Systems Thinking into the Classroom", *International Journal of Science Education*, Vol. 42, No. 8, pp. 1253-1280.
- Gobert, J.D. and J.J. Clement, 1999, "Effects of Student-Generated Diagrams versus Student-Generated Summaries on Conceptual Understanding of Causal and Dynamic Knowledge in Plate Tectonics", *Journal of Research in Science Teaching*:

The Official Journal of the National Association for Research in Science Teaching, Vol. 36, No. 1, pp. 39-53.

Gobert, J.D., 2005, "The Effects of Different Learning Tasks on Model-Building in Plate Tectonics: Diagramming Versus Explaining", *Journal of Geoscience Education*, Vol. 53, No. 4, pp. 444-455.

Gray, S., E.J. Sterling, P. Aminpour, L. Goralnik, A. Singer, C. Wei, S. Akabas, R.C. Jordan, P.J. Giabbanelli, J. Hodbod, E. Betley, and P. Norris, 2019, "Assessing (Social-Ecological) Systems Thinking by Evaluating Cognitive Maps", *Sustainability*, Vol. 11, No. 20, pp. 5753-5774.

Grohs, J.R., G.R. Kirk, M.M. Soledad, and D.B. Knight, 2018, "Assessing Systems Thinking: A Tool to Measure Complex Reasoning Through Ill-Structured Problems", *Thinking Skills and Creativity*, Vol. 28, No. 1, pp. 110-130.

Haque, S., H. Mahmoudi, N. Ghaffarzadegan, and K. Triantis, 2023, "Mental Models, Cognitive Maps and the Challenge of Quantitative Analysis of Their Network Representations", *System Dynamics Review*, Vol. 39, No. 2, pp. 152-170.

Haraldsson, H.V., 2004, *Introduction to System Thinking and Causal Loop Diagrams*, Department of Chemical Engineering, Lund University.

Herman, B.C., A. Feldman, and V. Vernaza-Hernandez, 2017, "Florida and Puerto Rico Secondary Science Teachers' Knowledge and Teaching of Climate Change Science", *International Journal of Science and Mathematics Education*, Vol. 15, No. 1, pp. 451-471.

Hmelo-Silver, C.E., S. Marathe, and L. Liu, 2007, "Fish Swim, Rocks Sit and Lungs Breathe Expert-Novice Understanding of Complex Systems", *The Journal of the Learning Sciences*, Vol. 16, No. 3, pp. 307-331.

- Hung, W., 2008, “Enhancing Systems Thinking Skills with Modeling”, *British Journal of Educational Technology*, Vol. 39, No. 6, pp. 1099-1120.
- Ignacio, J.T.S., C.K. Gotangco Gonzales, and Q. Lee-Chua, 2023, *A Systems Thinking Approach to E-Learning on Climate Change: Capacity-Building for Junior High School Teachers in the Philippines*, *International Journal of Disaster Resilience in the Built Environmen*
- Intergovernmental Panel on Climate Change (IPCC), 2014, “Climate Change 2014: Synthesis Report, Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change”, *Intergovernmental Panel on Climate Change (IPCC)*, Geneva, Switzerland, Vol. 151, No. 1, pp. 145-167.
- Intergovernmental Panel on Climate Change IPCC. 2023, “Summary for Policymakers. In: Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change, Intergovernmental Panel on Climate Change (IPCC)”, *Geneva, Switzerland*, Vol. 1, No. 1, pp. 1-34.
- Jeong, A. and W.J. Lee, 2012, “Developing Causal Understanding with Causal Maps: The Impact of Total Links, Temporal Flow and Lateral Position of Outcome Nodes”, *Educational Technology Research and Development*, Vol. 60, No. 1, pp. 325-340.
- Jonassen, D.H. and I.G. Ionas, 2008, “Designing Effective Supports for Causal Reasoning”, *Educational Technology Research and Development*, Vol. 56, No. 1, pp. 287-308.
- Kahan, D.M., H. Jenkins-Smith, and D. Braman, 2011, “Cultural Cognition of Scientific Consensus”, *Journal of Risk Research*, Vol. 14, No. 2, pp. 147-174.

- Karaarslan Semiz, G. and G. Teksöz, 2019, “Sistemsel Düşünme Becerilerinin Tanımlanması, Ölçülmesi ve Değerlendirilmesi Üzerine Bir Çalışma: Kavram Haritaları”, *Başkent University Journal of Education*, Vol. 6, No. 1, pp. 111-126.
- Karga, B. and G.D. Ceyhan, 2024, “Investigating Middle School Science Teachers’ Stock-Flow, Causal-Loop and Dynamic Thinking Skills with Scenario-Based Questions”, *International Journal of Science Education*, Vol. 1, No. 1, pp. 1-20.
- Kim, D.H., 1999, *Introduction to Systems Thinking*, Pegasus Communications, Waltham.
- Kim, H. and D.F. Andersen, 2012, “Building Confidence in Causal Maps Generated from Purposive Text Data: Mapping Transcripts of the Federal Reserve”, *System Dynamics Review*, Vol. 28, No. 4, pp. 311-328.
- Lane, D.C., 2008, “The Emergence and Use of Diagramming in System Dynamics: A Critical Account”, *Systems Research and Behavioral Science: The Official Journal of the International Federation for Systems Research*, Vol. 25, No. 1, pp. 3-23.
- Lane, A., 2013, “A Review of Diagramming in Systems Practice and How Technologies Have Supported the Teaching and Learning of Diagramming for Systems Thinking in Practice”, *Systemic Practice and Action Research*, Vol. 26, No. 1, pp. 319-329.
- Lavi, R., and Y.J. Dori, 2019, “Systems Thinking of Pre-And In-Service Science and Engineering Teachers”, *International Journal of Science Education*, Vol. 41, No. 2, pp. 248-279.
- Lee, T.D., 2015, *Science Teachers’ Representational Competency and Systems Thinking*, North Carolina State University, United States of America.
- Lee, T.D., M. Gail Jones, and K. Chesnutt, 2019, “Teaching Systems Thinking in the Context of the Water Cycle”, *Research in Science Education*, Vol. 49, No. 1, pp.

137-172.

Leung, J.S.C., M.M.W. Cheng, and P.Y.Y. Chik, 2024, “Fostering Systems Thinking About Socioscientific Issues”, *International Journal of Science Education*, Vol. 1, No. 1, pp. 1-19.

Liu, S., G. Roehrig, D. Bhattacharya, and K. Varma, 2015, “In-Service Teachers’ Attitudes”, *Knowledge and Classroom Teaching of Global Climate Change*, Vol. 24, No. 1, pp. 1-22.

Liu, S.C., 2022, “Examining Undergraduate Students’ Systems Thinking Competency through a Problem Scenario in the Context of Climate Change Education”, *Environmental Education Research*, Vol. 1, No. 1, pp. 1-16.

Lopes, R. and N. Videira, 2015, “Conceptualizing Stakeholders’ Perceptions of Ecosystem Services: A Participatory Systems Mapping Approach”, *Environmental and Climate Technologies*, Vol. 16, No. 1, pp. 36-53.

McCrudden, M.T., G. Schraw, S. Lehman, and A. Poliquin, 2007, “The Effect of Causal Diagrams on Text Learning”, *Contemporary Educational Psychology*, Vol. 32, No. 3, pp. 367-388.

Mambrey, S., J. Timm, J.J. Landskron, and P. Schmiemann, 2020, “The Impact of System Specifics on Systems Thinking”, *Journal of Research in Science Teaching*, Vol. 57, No. 10, pp. 1632-1651.

Meadows, D.H., 2008, *Thinking in Systems: A primer*, Chelsea Green Publishing, Florida.

Monroe, M.C., R.R. Plate, A. Oxarart, A. Bowers, and W.A. Chaves, 2019, “Identifying Effective Climate Change Education Strategies: A Systematic Review of the

Research”, *Environmental Education Research*, Vol. 25, No. 6, pp. 791-812.

Moser, S.C., 2010, “Communicating Climate Change: History, Challenges, Process and Future Directions”, *Wiley Interdisciplinary Reviews: Climate Change*, Vol. 1, No. 1, pp. 31-53.

Naugle, A., S. Verzi, K. Lakkaraju, L. Swiler, C. Warrender, M. Bernard, and V. Romero, 2023, “Feedback Density and Causal Complexity of Simulation Model Structure”, *Journal of Simulation*, Vol. 17, No. 3, pp. 229-239.

Nesbit, J.C. and O.O. Adesope, 2006, “Learning with Concept and Knowledge Maps: A Meta-Analysis”, *Review of Educational Research*, Vol. 76, No. 3, pp. 413-448.

Norris, M.B., J.R. Grohs, and D.B. Knight, 2022, “Investigating Student Approaches to Scenario-Based Assessments of Systems Thinking”, *Frontiers in Education*, Vol. 1, No. 1, pp. 7-19.

Owen, B., A.D. Brown, J. Kuhlberg, L. Millar, M. Nichols, C. Economos, and S. Allender, 2018, “Understanding a Successful Obesity Prevention Initiative in Children under 5 from a Systems Perspective”. *PloS One*, Vol. 13, No. 3, pp. e0195141-e0195161.

Plate, R., 2010, “Assessing Individuals’ Understanding of Nonlinear Causal Structures in Complex Systems”, *System Dynamics Review*, Vol. 26, No. 1, pp. 19-33.

Plate, R.R., 2006, *Assessing the Effectiveness of Systems-Oriented Instruction for Preparing Students to Understand Complexity*, Ph.D. Thesis, University of Florida.

Plutzer, E., M. McCaffrey, A.L. Hannah, J. Rosenau, M. Berbeco, and A.H. Reid, 2016, “Climate Confusion Among US Teachers”, *Science*, Vol. 351, No. 6274, pp. 664-665.

- Rakbamrung, P., P. Thepnuan, and N. Nujenjit, 2015, "Use of a System Thinking Learning Force and Motion Concept in Physics for Nurse Course", *Procedia-Social and Behavioral Sciences*, Vol. 197, No. 1, pp. 126-134.
- Richmond, B., 2000, *The Thinking in Systems Thinking: Seven Essential Skills*, Pegasus Communications, London.
- Rosenkränzer, F., C. Hörsch, S. Schuler, and W. Riess, 2017, "Student Teachers' Pedagogical Content Knowledge for Teaching Systems Thinking: Effects of Different Interventions", *International Journal of Science Education*, Vol. 39, No. 14, pp. 1932-1951.
- Rousell, D., and A. Cutter-Mackenzie-Knowles, 2020, "A Systematic Review Of Climate Change Education: Giving Children And Young People A Voice and A Hand'in Redressing Climate Change", *Children's Geographies*, Vol. 18, No. 2, pp. 191-208.
- Roychoudhury, A., D.P. Shepardson, and A.S. Hirsch, 2017, "System Thinking and Teaching in the Context of Climate System and Climate Change", *In Teaching and Learning About Climate Change*, Vol. 1, No. 1, pp. 29-42.
- Ruddiman, W.F., 2001, "Earth's Climate: Past and Future", *Macmillan*, Vol. 1, No. 1, pp. 576-589.
- Schaffernicht, M., 2007, "Causality and Diagrams for System Dynamics", *In Proceedings of the 25th International Conference of the System Dynamics Society July*, Paris.
- Schaffernicht, M. and S.N. Groesser, 2011, "A Comprehensive Method for Comparing Mental Models of Dynamic Systems", *European Journal of Operational Research*, Vol. 210, No. 1, pp. 57-67.

- Schmidt, J., L. Wollermann, S. Abele, and R. Müller, 2024, "Concept Maps to Assess System Understanding: Are Graphical Explanations More Accurate than Verbal Ones", *Behavioral Sciences*, Vol. 14, No. 9, pp. 807-834.
- Schultz, M., D. Chan, A.C. Eaton, J.P. Ferguson, R. Houghton, A. Ramdhan, O. Taylor, H.H. Vu, and Delaney, S., 2022, "Using Systems Maps to Visualize Chemistry Processes: Practitioner and Student Insights", *Education Sciences*, Vol. 12, No. 9, pp. 596-617.
- Senge, P.M., 1990, *The Fifth Discipline-The Arts and Practice of the Learning Organization*, Doubleday/Currency, New York.
- Shepardson, D.P., A. Roychoudhury, A. Hirsch, D. Niyogi, and S.M. Top, 2014, "When the Atmosphere Warms it Rains and Ice Melts: Seventh Grade Students' Conceptions of A Climate System", *Environmental Education Research*, Vol. 20, No. 3, pp. 333-353.
- Shin, H.S. and A. Jeong, 2021, "Modeling the Relationship between Students' Prior Knowledge, Causal Reasoning Processes and Quality of Causal Maps", *Computers and Education*, Vol. 163, No. 1, pp. 104113-104125.
- Sibley, D.F. and C.W. Erson, M. Heidemann, J.E. Merrill, J.M. Parker, and D.W. Szymanski, 2007, "Box Diagrams to Assess Students' Systems Thinking About the Rock, Water and Carbon Cycles", *Journal of Geoscience Education*, Vol. 55, No. 2, pp. 138-146.
- Sterling, S., 2008, "Sustainable Education - Towards A Deep Learning Response to Unsustainability", *Policy and Practice: A Development Education Review*, Vol. 6, No. 1, pp. 63-68.
- Sterman, J.D., 2002, "All Models Are Wrong: Reflections on Becoming A Systems

Scientist”, *System Dynamics Review*, Vol. 18, No. 4, pp. 501-531.

Sterman, J.D., 2000, *System Dynamics: Systems Thinking and Modeling for a Complex World*, MIT Sloan School of Management, Cambridge.

Sterman, J.D., 2001, “System Dynamics Modeling: Tools for Learning in a Complex World”, *California Management Review*, Vol. 43, No. 4, pp. 8-25.

Sterman, J.D., 1994, “Learning in and About Complex Systems”, *System Dynamics Review*, Vol. 10, No. 2-3, pp. 291-330.

Sterman, J.D., 2011, “Communicating Climate Change Risks in a Skeptical World”. *Climatic Change*, Vol. 108, No. 1, pp. 811-826.

Sterman, J.D., and L.B. Sweeney, 2002, “Cloudy Skies: Assessing Public Understanding of Global Warming”, *System Dynamics Review: The Journal of the System Dynamics Society*, Vol. 18, No. 2, pp. 207-240.

Stevenson, R.B., J. Nicholls, and H. Whitehouse, 2017, “What is Climate Change Education”, *Curriculum Perspectives*, Vol. 37, No. 1, pp. 67-71.

Strapasson, A., M. Ferreira, D. Cruz-Cano, J. Woods, M.P. do Nascimento Maia Soares, and O.L. da Silva Filho, 2022, “The Use of System Dynamics for Energy and Environmental Education”, *International Journal of Educational Technology in Higher Education*, Vol. 19, No. 1, pp. 5-24.

Sweeney, L.B. and J.D. Sterman, 2000, “Bathtub Dynamics: Initial Results of a Systems Thinking Inventory”, *System Dynamics Review: The Journal of the System Dynamics Society*, Vol. 16, No. 4, pp. 249-286.

Sweeney, L.B. and J.D. Sterman, 2007, “Thinking About Systems: Student and Teacher

Conceptions of Natural and Social Systems”, *System Dynamics Review: The Journal of the System Dynamics Society*, Vol. 23, No. 2-3, pp. 285-311.

Szozda, A.R., K. Bruyere, H. Lee, P.G. Mahaffy, and A.B. Flynn, 2022, “Investigating Educators’ Perspectives toward Systems Thinking in Chemistry Education from International Contexts”, *Journal of Chemical Education*, Vol. 99, No. 7, pp. 2474-2483.

Szozda, A.R., P.G. Mahaffy, and A.B. Flynn, 2023, “Identifying Chemistry Students’ Baseline Systems Thinking Skills When Constructing System Maps for a Topic on Climate Change”, *Journal of Chemical Education*, Vol. 100, No. 5, pp. 1763-1776.

Thibodeau, P.H., C.M. Frantz, and M.L. Stroink, 2016, “Situating a Measure of Systems Thinking in a Landscape of Psychological Constructs”, *Systems Research and Behavioral Science*, Vol. 33, No. 6, pp. 753-769.

Tripto, J., O.B.-Z. Assaraf, and M. Amit, 2013, “Mapping what They Know: Concept Maps as an Effective Tool for Assessing Students’ Systems Thinking”, *American Journal of Operations Research*, Vol. 3, No. 1, pp. 245-258.

Tripto, J., O.B.Z. Assaraf, Z. Snapir, and M. Amit, 2017, “How is the Body’s Systemic Nature Manifested Amongst High School Biology Students”, *Instructional Science*, Vol. 45, No. 1, pp. 73-98.

Tolppanen, S. and S. Kärkkäinen, 2021, “The Blame-Game: Pre-Service Teachers Views on Who Is Responsible and What Needs to be done to Mitigate Climate Change”, *International Journal of Science Education*, Vol. 43, No. 14, pp. 2402-2425.

United Nations Educational, Scientific and Cultural Organization (UNESCO), 2021, *Skills Development and Climate Change Action Plans*, Enhancing TVET’s Contri-

bution.

United Nations Educational, Scientific and Cultural Organization (UNESCO), 2017, *Education for Sustainable Development Goals*, Learning Objectives.

Wasserman, J.A. and J. Banks, 2017, “Details and Dynamics: Mental Models of Complex Systems in Game-Based Learning”, *Simulation and Gaming*, Vol. 48, No. 5, pp. 603-624.

World Economic Forum, 2023, *The Global Risks Report*, World Economic Forum Cologny, Switzerland.

Yin, R., 2014, *Case Study Research: Design and Methods*, CA: Sage, Oaks.

York, S., R. Lavi, Y.J. Dori, and M. Orgill, 2019, “Applications of Systems Thinking in STEM Education”, *Journal of Chemical Education*, Vol. 96, No. 12, pp. 2742-2751.

York, S., and M. Orgill, 2020, “ChEMIST Table: A Tool for Designing or Modifying Instruction for a Systems Thinking Approach in Chemistry Education”, *Journal of Chemical Education*, Vol. 97, No. 8, pp. 2114-2129.

APPENDIX A: DEMOGRAPHIC FORM

Below is an example of demographic form.

Name:

Gender: Female / Male / Other

Department:

- ☐ Foreign Language Education
- ☐ Preschool Education
- ☐ Primary Mathematics Education
- ☐ Primary Science Education
- ☐ Secondary Chemistry Education
- ☐ Secondary Mathematics Education
- ☐ Secondary Physics Education

Have you ever taken a course about climate change? Yes / No

APPENDIX B: ADAPTED VERSION OF LAKE URMIA VIGNETTE

Below is the adapted version of Lake Urmia Vignette.

(For the purposes of this study, this tool was adapted from Davis *et al.* (2020) by re-asking the existing questions to answer them by drawing causal loop diagrams)

The Lake Urmia vignette

Lake Urmia in north-west Iran was the largest lake in the Middle East and the sixth largest saltwater lake on earth. Unique ecological features of this UNESCO Biosphere Reserve had made Urmia the largest habitat of brine shrimp. The Lake is the home of various species of Archaeobacteria and Bacteria, Microfungi, Phytoplankton, and 311 species of Plants. It also hosts 226 kinds of Birds. The lake is also known for its hundreds of small islands serving as stopover points during the migrations of several wild birds to and from Russia. The town Urmia, on the west side of the lake, has a population of 700,000 people.

Several reports show that the lake suffers from serious ecological problems, and many of the indicators are easily observable from the lake itself. Between 1972 and 2014, the area of the lake shrank by 88%. The evaporation of the water has exposed the lakebed and caused windblown salt, which may lead to environmental health crises, including increase in infant mortality, cancer, and liver, kidney, and respiratory diseases. This phenomenon is similar to what happened after the death of the Aral Sea. In addition, it will increase unemployment by reducing tourism and shrinking the fertility of the land in the region.

Fortunately, the public awareness about the lake has increased and huge outcries urged the government to take action. Government officials promised to

spend \$5 million to save the lake in a period of 10 years. Officials attribute the lake's desiccation to the drought in recent years while critics point to mismanagement of water resources and construction of a raised road across the lake. The population of the region more than tripled during the past 40 years. Multiple dam construction and pipe transfer projects have made water available for domestic and agricultural purposes. In 1999, a project was completed to pump water from the Zarinneh River (one of the main feeders of the lake) to the largest city of the area. In addition, forests have been transferred to agricultural lands to fulfill the needs of the growing population. Specifically, the forest cover of Zagros Mountain has declined. Forests of Zagros maintain naturally controlled water flow to rivers feeding the lake. As the lake shrinks, the climate of the region becomes drier and more water is needed for agriculture.

In 2011, multiple demonstrations took place in cities close to the lake demanding that the government take immediate actions to protect Urmia Lake. Not all demonstrations ended peacefully. The slogan "let me cry to fill the lake", a highly chanted motto depicted the emotional reaction of the region. According to official state reports at least 70 supporters of the lake were arrested. Several proposals were discussed including channeling water from other rivers to the lake, destroying several dams, or funding relocation of people living around the Lake. In order to find solutions for saving the lake, policy makers need to know what caused the lake to shrink by 88% in 44 years. The lake is just an example of many similar environmental challenges that humans are dealing with especially in less developed regions.

Table B.1. Descriptives statistics of participants.

Q1. What do you think ‘went wrong’ in Lake Urmia? Based on the provided text, and your own thoughts, write an explanation on why Urmia is suffering from its problems.
Q2. What do you think ‘went wrong’ in Lake Urmia? Based on the provided text, and your own thoughts please create or show causal loops.
Q3. Given the problem, what should be done to protect the environment and ecosystem of Lake Urmia? Please write an explanation.
Q4. Given the problem, what should be done to protect the environment and ecosystem of Lake Urmia? Please create or show causal loops.

APPENDIX C: ETHICAL APPROVAL FROM BOGAZICI UNIVERSITY

Ethical approval was obtained from Bogazici University.



T.C.
BOĞAZİÇİ ÜNİVERSİTESİ REKTÖRLÜĞÜ
Fen Bilimleri ve Mühendislik Alanları İnsan Araştırmaları Etik Kurulu (Fminarek)



Sayı : E-84391427-050.01.04-167473
Konu : 2024/05 Kayıt no'lu başvurunuz hakkında

14.02.2024

Sayın Dr. Öğr. Üyesi Gaye Defne CEYHAN

"Examining the Mental Models of Pre-service Teachers on a Climate Change Based Case Scenario with the Systems Thinking Approach" başlıklı projeniz ile Boğaziçi Üniversitesi Fen Bilimleri ve Mühendislik Alanları İnsan Araştırmaları Etik Kurulu (FMINAREK)'ye yaptığınız 2024/05 kayıt numaralı başvuru 05.02.2024 tarihli ve 2024/02 No.lu kurul toplantısında incelenerek etik onay verilmesi uygun bulunmuştur.

Bu karar tüm üyelerin toplantıya on-line olarak katılımıyla ve oybirliği ile alınmıştır. Onay mektubu tüm üyeler adına Komisyon Başkanı tarafından e-imzalanmıştır. Bilginize sunarız.

Saygılarımızla,

Prof. Dr. Tınaz EKİM AŞICI
Kurul Başkanı

Bu belge, güvenli elektronik imza ile imzalanmıştır.

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Telefon No: Fax No:
e-Posta: www.bogazici.edu.tr
Kep Adresi: bogaziciuniversitesi@hs01.kep.tr

Bilgi İçin: Nurgün MUNAR
Mühendis

Telefon No:



Figure C.1. Ethical approval was obtained from Bogazici University.

formu doldurmanızı isteyeceğiz. Demografik form yaşıınız, cinsiyetiniz, bölümünüz ve çevre eğitimi ile ilgili önceki ders deneyimleriniz hakkında sorulardan oluşmaktadır. İkinci olarak, size gerçek hayattan bir sorunla ilgili bir senaryo sunulacaktır. Senaryo ile ilgili 4 açık uçlu soruya yanıt vermeniz beklenmektedir. Çalışma boyunca ikili gruplar halinde çalışacaksınız. Soruların yanıtlanma süresi yaklaşık 50 dakika olarak planlanmaktadır. Bu sorulara vereceğiniz yanıtlar araştırma verisi olarak kullanılacaktır. Bu araştırma bilimsel bir amaçla yapılmaktadır ve katılımcı bilgilerinin gizliliği esas tutulmaktadır.

Araştırma tamamlandıktan sonra dosyalarınız kilitli bir dolapta muhafaza edilecek ve araştırmacılar dışında verileriniz kesinlikle üçüncü kişilerle paylaşılmayacaktır. Bu araştırmaya katılım tamamen gönüllülük esasına dayanmaktadır. Bu çalışmaya katıldığınız takdirde herhangi bir ücret veya bir ödül almayacağınızı belirtmek isteriz. Araştırmanın sizin için bir risk oluşturması beklenmemektedir. Çalışmaya katıldığınız takdirde çalışmanın herhangi bir aşamasında herhangi bir sebep göstermeden onayınızı çekme hakkına sahipsiniz. Çalışmadan çekilmek istediğinizde verileriniz tamamen silinecektir ve hiçbir yerde paylaşılmayacaktır. Araştırma hakkında ek bilgi almak isterseniz lütfen Boğaziçi Üniversitesi Matematik ve Fen Bilimleri Eğitimi Bölümü Öğretim Üyesi Dr. Gaye Defne Ceyhan, (e-mail: gaye.cejhan@boun.edu.tr, Adres: Boğaziçi Üniversitesi, Kuzey Kampüs ETA B 414, Bebek, İstanbul) veya yüksek lisans öğrencisi Nazmiye Ertuğrul, (e-mail: nazmiye.ertugrul@boun.edu.tr) ile iletişime geçiniz. Ayrıca, bu araştırmadaki haklarınız hakkında daha fazla bilgi almak için Boğaziçi Üniversitesi Fen Bilimleri ve Mühendislik Alanları İnsan Araştırmaları Etik Kurulu'na (fminarek@boun.edu.tr) da danışabilirsiniz.

Eğer bu araştırmaya katılmayı kabul ediyorsanız, lütfen bu formu imzalayıp kapalı bir zarf içerisinde bize geri veriniz.

Ben, (katılımcının adı), yukarıdaki metni okudum ve katılmam istenen çalışmanın kapsamını ve amacını, gönüllü olarak üzerime düşen sorumlulukları tamamen anladım. Çalışma hakkında soru sorma imkanı buldum.

Bu çalışmayı istediğim zaman ve herhangi bir neden belirtmek zorunda kalmadan bırakabileceğimi ve bıraktığım takdirde herhangi bir olumsuzluk ile karşılaşmayacağımı anladım.

Bu koşullarda söz konusu araştırmaya kendi isteğimle, hiçbir baskı ve zorlama olmaksızın katılmayı kabul ediyorum.

EVET / HAYIR

Formun bir örneğini aldım / almak istemiyorum (bu durumda araştırmacı bu kopyayı saklar).

Katılımcının Adı-Soyadı:.....

İmzası:.....

Adresi (varsa Telefon No, Faks No):.....

Tarih (gün/ay/yıl):...../...../.....

Araştırmacının Adı-Soyadı: Nazmiye Ertuğrul

İmzası:.....

Tarih (gün/ay/yıl):...../...../.....

APPENDIX E: PROCEDURE OF DATA ANALYSIS

The Figure E.1, illustrates the procedure of data analysis

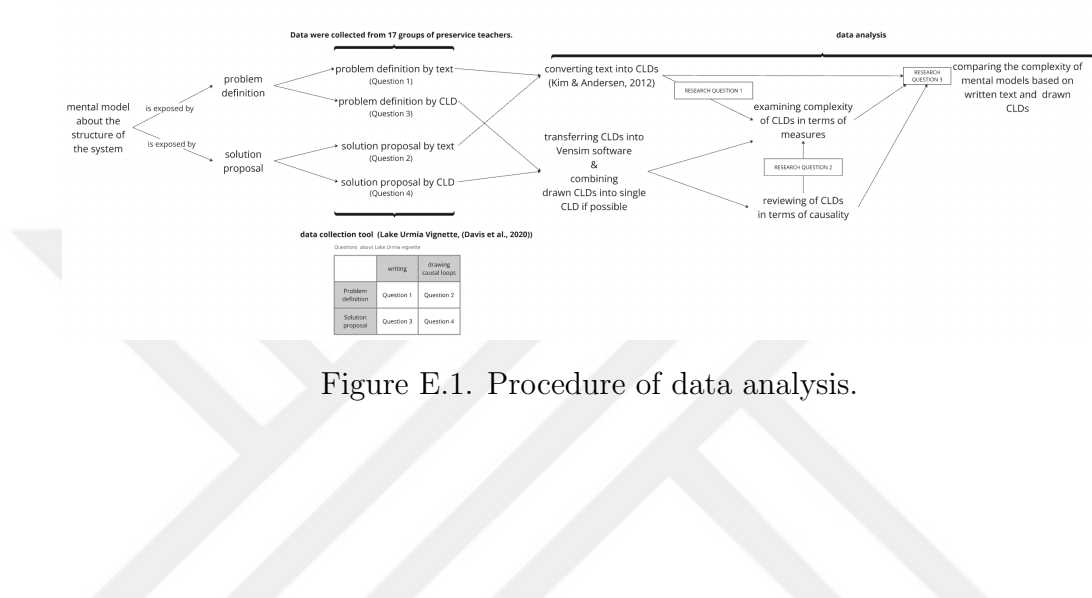


Figure E.1. Procedure of data analysis.

APPENDIX F: AN EXAMPLE OF CODING PROCEDURE FOR WRITTEN RESPONSES

(Adapted by Haque *et al.*, 2023).

The Figure F.1. illustrates an example of coding procedure for written responses.

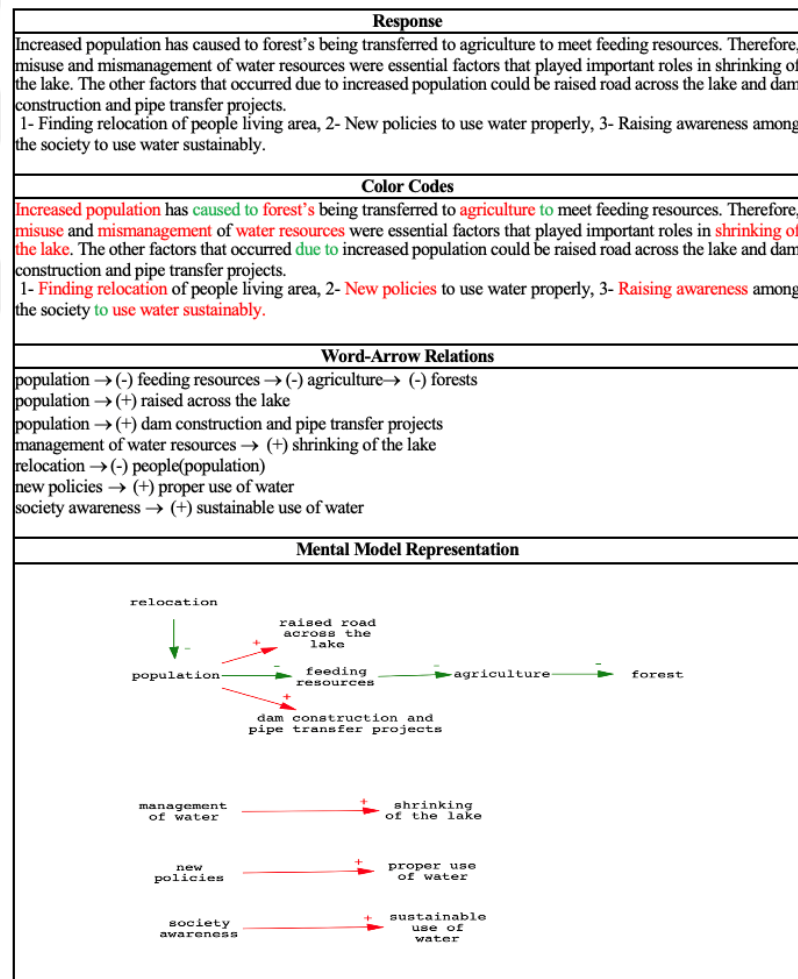


Figure F.1. An example of coding procedure for written responses.

APPENDIX G: AN EXAMPLE FOR ANALYSIS OF CLDS DRAWN BY EACH GROUPS

The Figure G.1. illustrates an example for analysis of clds drawn by each group.

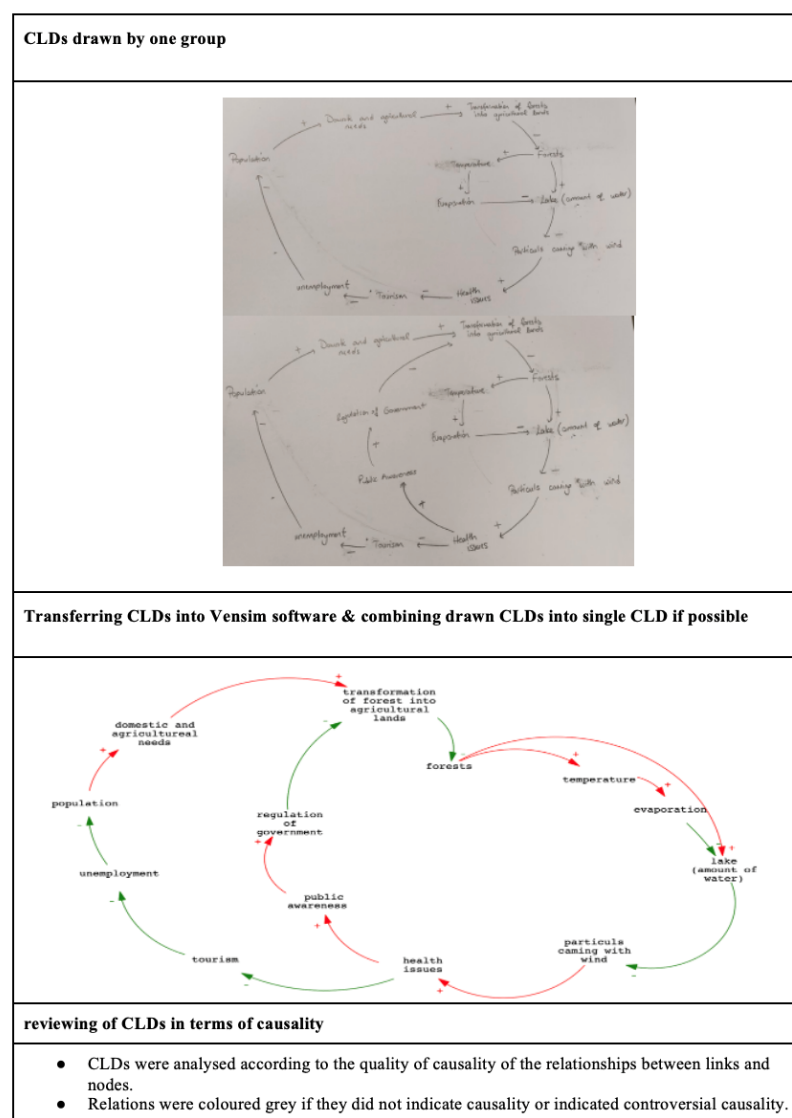


Figure G.1. An example for analysis of clds drawn by each group.

APPENDIX H: COMPARISON OF MEASURES OF PARTICIPANTS' MENTAL MODELS DERIVED FROM WRITTEN EXPLANATIONS (TEXT) AND DRAWN CLDS

The Figure H.1. illustrates the comparison of measures of participants' mental models derived from written explanations (text) and drawn clds

Groups	Link Density		Web-Like Causality Index		Feedback Density		Cyclomatic Complexity		Causal Complexity	
	Written Response	Drawn CLDs	Written Response	Drawn CLDs	Written Response	Drawn CLDs	Written Response	Drawn CLDs	Written Response	Drawn CLDs
1	0,69	1,17	0,077	0,417	0	1	4	4	4	8
2	1	1,13	0,316	0,375	0	0,53	4	3	4	4,59
3	1,11	1,29	0,263	0,529	0	1	4	7	4	14
4	0,85	1,31	0,077	1	0	0	2	8	2	8
5	0,79	1,14	0,167	0,357	0	0,63	3	4	3	6,53
6	0,75	1,15	0,125	0,308	0	1	4	4	4	8
7	1,08	1,5	0,583	0,5	0	0	3	8	3	8
8	1,13	1,13	0,375	0,267	0	1	3	4	3	8
9	0,89	0,88	0,222	0,111	0	0	3	1	3	1
10	1	1,05	0,294	0,3	0	0,34	2	3	2	4,02
11	0,9	1,17	0,2	0,5	0	0	2	4	2	4
12	0,8	1,08	0,1	0,25	0	0,84	2	3	2	5,52
13	0,91	2,09	0,273	0,917	0	0,59	6	14	6	22,24
14	0,93	1,17	0,214	0,333	0	1	3	4	3	8
15	1	1,08	0,227	0,231	0	0,56	4	3	4	4,67
16	0,67	1,63	0,111	0,75	0	0,2	4	12	4	14,34
17	0,86	1,25	0,286	0,5	0	0	1	4	1	4

Figure H.1. Comparison of measures of participants' mental models derived from written explanations (text) and drawn clds.