Master's Thesis

Master Sustainable Business and Innovation

To which extent does the mental model complexity of climate change causes and consequences differ between regions (Lake Victoria and Lagos), gender, and levels of risk perception?

Charlotte van Hal
Master Sustainable Business and Innovation
Faculty of Geosciences, Utrecht University
GEO4-2606 – Master's Thesis

Supervisor: Dr. Karlijn van den Broek
Second assessor: Dr. Maryse Chappin

25 August 2023

Word count: 21 039

Abstract

Humanity is increasingly facing the prospect of vastly changing environmental conditions. Determining viable mitigation and adaptation strategies toward climate change consequences necessitates an understanding that appropriately reflects human's internal perception. Mental models (MM) are individuals' internal, intuitive understanding of a system. MM are cognitive systems in which nodes represent concepts and edges are the direct links between concepts, called causal relations. MM mapping can reveal differences in MM complexity, which refers to the amount of included concepts and causal relations. A more complex MM suggests a comprehensive understanding and awareness of the interconnectedness of various climate change causes and consequences, enabling people to make better-informed decisions regarding climate change mitigation.

This study investigates differences in MM complexity of climate change in Lake Victoria and Lagos. Identifying such differences can facilitate the development of effective communication strategies and policies to mitigate the impacts of climate change. The study employed a quantitative cross-sectional survey design to examine differences in the MM complexity of climate change. A quota non-probability sampling method was applied to recruit participants from the Lake Victoria region (*Tanzania, Uganda, Kenya)* (N = 642) and Lagos (N = 352). The study instrument consisted of the M-Tool method to elicit MM and a questionnaire.

The study results indicate that people tend to have a more comprehensive understanding of the potential consequences of climate change as opposed to its causes. This implies that individuals may not fully understand the mechanisms causing it. The research did not find a consistent relationship between gender significantly explaining complexity differences in MM of climate change causes and consequences. Furthermore, the study found that people who perceived a higher climate change risk did not consistently tend to have a more complex MM.

The empirical evidence provided by this study extends the existing literature on MM complexity. The study's findings may be used to enlarge the MM complexity of climate change causes in both regions, the amount of included concepts for women in Lake Victoria, and lastly, people with a lower perceived risk in Lagos for the inclusion of more concepts at the MM of the causes and consequences of climate change and in Lake Victoria for the inclusion of more concepts at the MM of the consequences of climate change. The findings indicate the need for tailored communication strategies considering differences in MM complexity. This approach expects to promote action and cooperation in mitigating climate change.

Keywords*: mental models, mental model complexity differences, climate change, climate change mitigation, causes of climate change, consequences of climate change, psychological perception of climate change*

Table of Contents

1. Introduction

As the scientific consensus on anthropogenic climate change has become unequivocal (IPCC, 2007), humanity is increasingly facing the prospect of vastly changing environmental conditions. Subsequently, a crucial obstacle in learning towards and maintaining a sustainable future is the challenge of enabling effective mitigation and adaptation measures under such changing conditions (Helgeson et al., 2012). Climate change represents a complex set of challenges, predominantly because it is marked by risks not easily observed and identified – risks humans have difficulty estimating. Determining viable mitigation and adaptation strategies toward climate change consequences thus necessitates an understanding that appropriately reflects human's internal perception (Helgeson et al., 2012).

A mental model (MM) is a person's inner, personalized, intuitive, and contextual understanding of how something works (Kearney and Kaplan, 1997). It is essential to consider how individuals learn, understands, and form mental representations of climate change, as MM help formulate actions and behavior (Carey 1986, Morgan et al. 2002). MM mapping can elicit internal, cognitive understandings of a system (Jones et al., 2011). Differences in MM may reflect disagreement about the causes and consequences of climate change. As a result, differences in MM can have significant implications for climate change policy support when there is disagreement about the perceived causes. For example, those who perceive carbon emissions to drive climate change were more likely to support policies reducing those emissions than those who attribute climate change to other causes (Bostrom et al., 2012). MM complexity is measured through the number of concepts and the connectivity between those concepts, called causal relations (van den Broek et al., 2023). The more concepts and causal relations included, the more coherent someone understands a system (Gray et al., 2015; Nadkarni & Narayanan, 2005). However, it is important to recognize that complexity does not always indicate a greater understanding. This is because individuals with higher levels of system-thinking expertise have the ability to simplify complex relationships, leading to a less complex MM (Levy et al., 2018; Hallbrendt et al., 2014).

To summarize, MM content differences thus refer to variations in the concepts included in a MM (Bostrom et al., 2012), while differences in MM complexity refers to variation in the amount of concepts and causal relations included between people (van den Broek et al., 2023; Gray et al., 2015; Nadkarni & Narayanan, 2005). Understanding the complexity of MM provides insights into how capable people are of processing and integrating information (Uitdewilligen et al., 2021). The latter is essential since climate change consequences bring along the need to adapt to a rapidly changing climate (Driver & Streufert, 1969).

To understand how African communities can avert climate change, it is necessary to understand their environmental perceptions. Consequently, this research aimed to understand what predicts a difference in MM complexity. The MM complexity is assessed in two African regions severely impacted by climate change: Lake Victoria and Lagos (Müller et al., 2014). Thus, the research explores how MM differs per region and which characteristics cause a variation in MM complexity.

To date, solely one study has been conducted on the complexity of MM in Lake Victoria. This study investigated the differences among Tanzanian fishermen in their understanding of the drivers of Nile perch stock fluctuations (van den Broek et al., 2023). Notably, the MM complexity of climate change causes and consequences has not been studied yet in Lake Victoria and Lagos. Additionally, there is a gap in the current literature regarding a study of the MM complexity of climate change in both regions. Thus, such a study would enhance the theoretical understanding of regional differences in MM complexity.

Moreover, there is an expected relationship between gender and MM complexity regarding climate change. While women tend to be more concerned about climate change and seek out information, it is unclear whether this leads to more complex MM than men, as suggested by a single study conducted by Ballew et al. (2018). Their study results of a sample representing American adults indicate that women were less likely than men to possess specific scientific knowledge about climate change, and tended to be less certain of what they know (Ballew et al., 2018).

The potential effect of gender on MM complexity remained ambiguous: therefore, the current study contributed to academic literature on whether men or women hold more complex MM. Moreover, there has been no previous research on differences in MM complexity between gender in Africa. This research sheds light on the previously unknown relationship between gender and MM complexity, making a valuable theoretical contribution.

Lastly, this study explored how people's level of perceived risk affected their MM complexity of climate change. Understanding risk perception is critical because it affects people's willingness to take action on climate change (Spence et al., 2012). A higher level of perceived risk is expected to associate with more detailed MM, while a lower level of perceived risk is expected to lead to simplified models (McDonald et al., 2015; Trope and Liberman, 2010). This study can provide insight into how risk perception affects the MM complexity of climate change. This, in turn, can inform communication efforts aimed at groups with lower risk perception and potentially less willingness to take action to mitigate climate change.

Accordingly, the following research question is raised:

To which extent does the mental model complexity of climate change causes and consequences differ across regions (Lake Victoria and Lagos), gender, and levels of risk perception?

Derived from the literature presented in the subsequent paragraph, the following sub-questions are raised:

Question 1: What do the mental models of the causes and consequences of climate change in Lagos and Lake Victoria look like?
Question 2: Does gender explain differences in mental model complexity?
Question 3: Does people's level of risk perception explain the mental model complexity?

This study will provide valuable insights into the relationship between gender, risk perception, and MM complexity of the causes and consequences of climate change. The results can inform the development of targeted communication strategies to encourage action on climate change (van den Broek et al., 2017; Cong Ngo, 2021). Moreover, communication efforts can be strategized by targeting specific stakeholder groups, leading to new knowledge and minimizing MM differences, thus fostering the innovative capacity needed to mitigate climate change (Blackman & Davidson, 2005). For example, a farmer's group representing agricultural interests would not adopt or be interested in the co-development of an innovation limiting the greenhouse gas emissions from a polluting agricultural practice with a partner who perceives deforestation as a single cause of climate change. Thus, when substantial MM differences can be bridged, the resulting shared understanding facilitates successful collaboration for development and sustainable business innovation (Blackman & Davidson, 2005).

2. Theory

2.1 Mental models of climate change

A mental model (MM) is a person's internal, personalized, intuitive, and contextual understanding of how something works (Kearney and Kaplan, 1997). MM are cognitive systems in which nodes represent concepts and edges are the direct links between concepts, called causal relations (Levy et al., 2018). MM are established through the experiences persons have with their surroundings; this allows persons to interact with and make sense of the world around them (Jones et al., 2011).

MM exists in the minds of individuals, and therefore, they cannot be directly analysed (Jones et al., 2011). Eliciting people's MM allows for understanding complex systems and the meanings people ascribe to them (Moon et al., 2019). Cognitive mapping is a technique to elicit MM: it represents a person's MM visually and presents how people structure their knowledge and beliefs (Axelrod, 1976).

Cognitive maps have two functions. First, the visual representation of the MM allows people to have a comprehensive view of the issue, making it easier to communicate and solve (Jetter & Kok, 2014). Secondly, the cognitive map can facilitate the discussion of new ideas and identify potential sources of differences between persons (Simcic Brønn & Brønn, 2003). Both functions are necessary for collaboration (Özesmi & Özesmi., 2004). Differences in MM between persons can refer to variations in the content and structure of MM (Bostrom et al., 2012) or differences in MM complexity, indicating that people include different amounts of information in their MM (van den Broek et al., 2023; Gray et al., 2015; Nadkarni & Narayanan, 2005).

It is essential to consider how people learn, understands, and form mental representations of climate change, as MM help formulate actions and behavior (Carey 1986, Morgan et al. 2002). Differences in MM about climate change may reflect disagreement about causes and solutions to climate change, leading to a lack of progress toward sustainable innovation. For instance, if businesses hold different MM about the impact of climate change, it could impede their ability to collaborate effectively. Negotiating these differences and developing a shared understanding can promote collaboration, allowing for more effective identification and implementation of innovations (Blackman & Davidson, 2005). Therefore, understanding MM is relevant for climate change research as considerable differences in MM can hinder the development of technologies to mitigate climate change impact (Bostrom et al., 2012). The application of MM for climate change research has demonstrated that it is a relevant framework for understanding perceptions of climate-related events (Bostrom et al., 2012).

2.2 Complexity differences in mental models

MM are complex when they include a high amount of concepts- and causal relations (Gray et al., 2015; Nadkarni & Narayanan, 2005). MM complexity is measured through the number of concepts included and the connectivity between those concepts. Subsequently, the MM can be similar or different when comparing groups (van den Broek et al., 2023). A higher MM complexity might indicate that the group has a better understanding of the system (Gray et al., 2015; Nadkarni & Narayanan, 2005).

However, MM complexity does not always indicate a more coherent understanding. Empirical evidence from Levy et al. (2018) did not find that expert knowledge resulted in more complex MM. Similarly, a comparative study by Hallbrendt et al. (2014) was unable to prove that MM from scientists regarding the perceived impacts of conservation agriculture were more complex than those of farmers. This may be because experts and scientists with a higher level of system-thinking capabilities have the ability to simplify complex relationships (Levy et al., 2018). Less complex MM may allow experts to focus on the most important causes, consequences, and causal relationships of climate change. Furthermore, people may include a high number of causal relationships in their MM of climate change, but the perceived relationships may not accurately reflect scientific reality (Levy et al., 2018), indicating that a more complex MM does not necessarily indicate more knowledge. If there is a mismatch between the way people perceive the dynamics of a system and the way it actually works, their policy preferences may be affected based on these misaligned MM (Gray, 2018).

Complex knowledge structures can be necessary for decision-making, specifically in complex and dynamic environments (Calori et al., 1994). There is a higher chance of a shared understanding of climate change and thus, collaboration for sustainable business innovation when a MM is more complex (Bostrom et al., 2012, Blackman & Davidson, 2005). Therefore, it is important to analyse differences in MM complexity.

According to Driver & Streufert (1969), MM complexity is influenced by the extent to which individuals seek sources of information, driven by the need to adapt to a dynamic changing environment. This information search will accordingly influence the structure of their MM with the new knowledge acquired (Tjosvold, 2008). Due to the consequences of extreme weather events, African regions experiencing severe climate change are expected to seek more information to adapt their livelihood (Hockerts, 2015), resulting in more perceived drivers and causal relations of climate change.

To clarify the conceptual understanding of MM content differences and MM complexity differences: MM content differences refer to the variations in the concepts included in a MM (Bostrom et al., 2012). For instance, two individuals may have different MM of climate change causes: with one person attributing industrialization as the primary cause, while the other person believes it is a natural phenomenon or due to God's will. This example demonstrates a content MM difference. On the other hand, differences in MM complexity indicate variation in the amount of included concepts and causal relations between individuals (van den Broek et al., 2023; Gray et al., 2015; Nadkarni & Narayanan, 2005). For example, when understanding climate change consequences, one person may have a simplified mental model that solely attributes a global temperature increase as a main consequence of climate change. The other person may have a highly detailed and interrelated mental model arguing that climate change results in rising sea levels, which subsequently can lead to erosion and flooding of coastal areas, while continuous hot weather can increase the risk of illnesses and deaths. The latter example demonstrates a more complex MM.

Thus, MM can have the same level of complexity but differ substantively in content which can still reflect disagreement about causes and solutions to climate change. However, the more complex a MM is, the more able people are to have a detailed understanding (Gray et al., 2015; Nadkarni &Narayanan, 2005), which in turn promotes collaboration and the development of sustainable business innovations to address climate change challenges (Bostrom et al., 2012, Blackman & Davidson, 2005). When individuals with a more complex MM aim to collaborate, the process is likely to require additional time compared to collaborations between individuals with a less complex MM. This is due to the evaluation of multiple causal relationships among system concepts. Nevertheless, the outcome of such collaborations is generally more effective, as individuals with a more complex MM are less likely to overlook outcomes beyond the most obvious causal relationships (Levy et al., 2018). Therefore, their thorough evaluation of causal relationships can lead to a deeper understanding of the system and can help identify potential issues and solutions that might have been overlooked otherwise.

MM complexity is explained by a variety of variables (Jones et al., 2011; Carey 1986, Morgan et al. 2002). Derived from a literature review (Atran., 2002; Axelrod et al, 1996; Ballew et al., 2018; Barnes, 2019; Grossman & Wood, 1993; Hoffman et al., 2014; Jones et al., 2011; Trope and Liberman, 2010), the variables *of risk perception and gender* are expected to be explanatory for differences in MM complexity of climate change. Other considered influential confounding variables are *age, education, and livelihood* (Bäthge, 2010; Calori et al., 1994; Denzin & North, 1992; Richert et al., 2016; Spence et al., 2012; Trope and Liberman, 2010). As a result, the subsequent sections will identify climate change impact in Lake Victoria and Lagos. Then, the effect of gender and risk perception potentially explaining variation in MM complexity of climate change causes and consequences will be elaborated upon.

2.3 Climate change impact in Lake Victoria and Lagos

2.3.1 Climate change impact and mental model complexity

The complexity of MM is influenced by the degree to which people actively seek out information in order to adapt to changing circumstances (Tjosvold, 2008). As people acquire new knowledge, their MM are accordingly enlarged. In regions of Africa experiencing severe climate change, the need to adapt livelihoods to extreme weather events is expected to drive an increased search for information about climate change (Hockerts, 2015), expected to result in more perceived drivers and causal relations of climate change. There is thus an expected correlation between climate change impact severity and MM complexity (Tjosvold, 2008; Hockerts, 2015).

The acquisition of new information is expected to accelerate when people need to adapt to a rapidly changing environment (Driver & Streufert, 1969). Subsequently, when this knowledge is integrated into their MM, it alternates the structure. It is necessary to understand the societal cognitive impact of climate change since a changing environment affects ecosystem functioning and the provision of ecosystem services (Müller et al., 2014), effective mitigation strategies are thus of considerable concern to human societies and economic development.

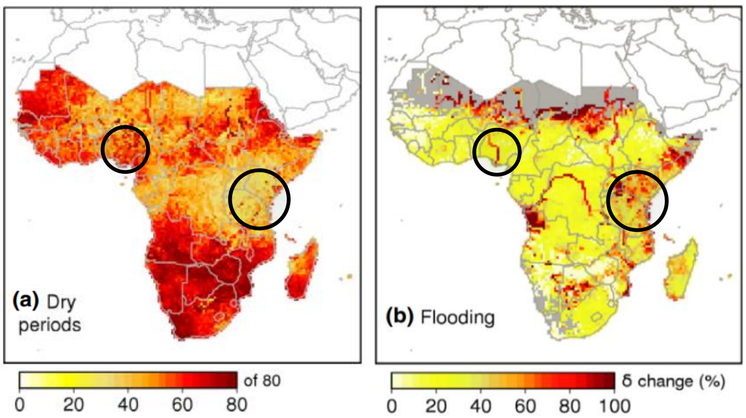
2.3.2 Climate change impact

The African continent has high vulnerability to a changing climate because of the prevalence of factors that increase the degree to which stress is experienced by the system, such as widespread poverty, overdependence on rain-fed agriculture, inequitable land distribution, and poor governance (Jones et al., 2015). This combination and a limited adaptive capacity due to budgetary constraints leave Africa vulnerable to climate change (Boko et al., 2007).

MM complexity will be assessed in two African regions severely impacted by climate change: Lake Victoria and Lagos (Müller et al., 2014). Climate change impacts in Lagos are mainly apparent through reduced total surface freshwater availability *(figure 1.a)*. Moreover, flooding probabilities are high-risk in both regions. In Lagos, predominantly areas near the Ogun river are at risk for flooding *(figure 1.b)*.

Figure 1

Climate change flooding-, dry periods- and impact severity in Sub-Saharan Africa (Müller et al., 2014): The circle on the right represents the region of Lake Victoria (Uganda, Tanzania and Kenya) the circle on the left represent the region Lagos.



Thus, both regions are expected to hold complex MM due to the new information people need to acquire to adapt to their changing environment due to climate change consequences (Tjosvold, 2008; Hockerts, 2015). Current study is the first to investigate MM complexity in Lagos, and it extends a single study investigating MM complexity in Lake Victoria (van den Broek et al., 2023). Specifically, van den

Broek et al. (2023) examined differences in MM complexity regarding the drivers of Nile perch stock fluctuations among Tanzanian fishermen. Current study extends this research by assessing differences in MM complexity related to climate change, thus a different system. Additionally, the sample in current study aims to generalize to the broader population of the region, in contrast to the sample of van den Broek et al. (2023) which consisted solely of fishermen. Thereby, this study contributes to the scientific body of literature investigating MM complexity in Lake Victoria and Lagos.

2.4 Complexity differences between mental models of the causes and consequences of climate change

MM complexity may differ when investigating the causes versus the consequences of climate change as local communities are already witnessing the effects of climate change (Haden et al., 2012; Spence et al., 2011). For example, people in Lake Victoria and Lagos experience more frequent and intensive droughts and rainfall (Müller et al., 2014). These local consequences are often more concrete and tangible than the remote causes that are frequently more distant on a global scale (Haden et al., 2012; Spence et al., 2011). As a result, people place greater emphasis on the immediate consequences of climate change, such as more frequent natural disasters, shifts in agricultural yields, and changes in weather patterns, while underemphasizing the fundamental causes, such as greenhouse gas emissions, deforestation, and other human activities that contribute to the problem. It is expected that this overemphasizes on climate change consequences and the subsequent acquired information will result in more complex MM of the consequences of climate change compared to the causes of climate change (Tjosvold, 2008).

Moreover, differences in MM complexity between the causes and consequences of climate change can occur since people may believe that they have greater control over the consequences of climate change than the causes. For example, people may consider taking actions to adapt to the consequences of climate change, such as exploring alternative economic activities when climate change threatens the longevity of one's livelihood or migrating to more fertile land. Also, one might feel disempowered addressing the root causes of climate change (Wolf & Moser, 2011; BBC, 2009), such as reducing global carbon emissions from industrial activities. This sense of control may incentivize people to pursue knowledge regarding the consequences of climate change, ultimately resulting in a greater level of MM complexity regarding the consequences of climate change in comparison to the causes of climate change (Tjosvold, 2008; Hockerts, 2015).

The following section will differentiate between the number of included concepts and causal relations in a person’s MM to measure complexity, allowing to hypothesize complexity differences comparing climate change causes and consequences for both parameters.

2.4.1 MM differences in concepts and causal relations between causes and consequences of climate change

Derived from the previously presented literature (Haden et al., 2012; Wolf & Moser, 2011; BBC, 2009; Spence et al., 2011; Tjosvold., 2008; Hockerts., 2015) it is expected that the MM of climate change consequences will be more complex compared to the causes, however, ambiguousness exists whether this applies to both the amount of included concepts and causal relations.

The results from a study by Lorenzoni and Pidgeon (2006) concluded that people may be hesitant to acquire new knowledge related to mitigating climate change due to the discomfort that occurs from the process of integrating this information into their daily lives. This discomfort can emerge from the challenge of accommodating new knowledge into an existing lifestyle. For example, people may be resistant to adopting behaviours to mitigate individual impact such as reducing their private transportation use or using less energy, as these behaviours may conflict with their current habits and lifestyles (Lorenzoni & Pidgeon, 2006). Consequently, this discomfort may result in people avoiding seeking out new information related to climate change causes. Thus, it is expected that people may rely on ‘vaguer’ descriptive concepts to describe the causes of climate change, as the discomfort associated with more integrated research may hinder acquiring a comprehensive understanding of the complex causal relations underlying climate change causes.

When people demonstrate a willingness to learn about the consequences of climate change, they may encounter difficulties in comprehending the full extent of its effects, particularly when they lack direct experience with those effects, this often occurs when the consequences are not experienced locally by the individual (Haden et al., 2012; Spence et al., 2011).

Many climate change consequences are global in scope and thus distant from the individual, whether in terms of geography, time, certainty, or social context (Trope & Liberman, 2010). An example of a distant perceived climate change consequence is the melting of ice gaps in the Rwenzori Mountains, Uganda (Taylor et al., 2007). While this may seem like a distant event for individuals living further away from the mountains, the melting of these ice gaps is expected to accelerate an increase in flooding and heightened sea-levels, affecting agriculture, food security, eco-tourism and the livelihoods of people in the region and downstream communities (Kaggwa et al., 2009). This sense of distance can lead to a lack of understanding of the severity of the consequences. Consequently, individuals may find it easier to identify more abstract concepts related to climate change consequences in their mental models while struggling to comprehend the underlying causal relationships due to the perceived sense of distance (Haden et al., 2012; Trope & Liberman, 2010).

These studies suggest that people find it easier to identify more concepts in their MM of climate change consequences compared to climate change causes. It is unknown whether people also include a larger amount of causal relations, since it is questionable whether people conduct integrated research to understand the complex relationships of climate change consequences beyond a local scale.

H_1: Mental models of climate change consequences consist of *more concepts* than mental models of climate change causes; literature is ambiguous on whether this also applies to *more causal relations.*

2.5 Gender and mental model complexity

Research suggests that there are gender-based differences in the MM of climate change between men and women, as evidenced by gender-based variations in perceptions of climate change (Pearson et al., 2017; Ballew et al., 2018;., Phelan et al., 2020).

Evidence suggesting whether men or women tend to hold more complex MM contrasts. According to Ballew et al. (2018), in the United States, research has shown that women exhibit a stronger perception of climate change's harmful effects compared to men. This heightened concern may motivate women to seek out more information, ultimately leading to a more complex understanding of climate change (Tjosvold, 2008; Hockerts, 2015). The expectation that women are more concerned about environmental threats coheres with findings from other studies. To illustrate, Pearson et al. (2017) demonstrated that women in the United States are more likely than men to be concerned about the environment and have stronger pro-climate opinions and beliefs. Thereby, women are more likely to perceive climate change as a proximal threat, potentially incentivizing them to seek information and enlarging the MM complexity (Tjosvold, 2008; Hockerts, 2015).

While women tend to be more concerned about climate change and seek out information, it is unclear whether this leads to more complex MM than men, as suggested by a single study conducted by Ballew et al. (2018). Their study results of a sample representing American adults indicate that women in the United States are less likely than men to possess certain scientific facts about global warming and tend to be less confident in their knowledge. Furthermore, women on average score lower than men in their scientific knowledge of climate change, including knowledge of specific facts about global warming (Ballew et al., 2018). Greater knowledge of scientific facts about climate change may lead to more complex MM, as it provides a deeper understanding of the underlying processes and causal mechanisms involved in climate change. This, in turn, could lead to the inclusion of a greater number of concepts and causal relationships within these models. (Gray et al., 2015; Nadkarni & Narayanan, 2005).

The finding that men may possess a greater degree of climate change knowledge is consistent with previous research by Phelan et al. (2020), who conducted a study to assess the level of knowledge about ocean plastic pollution among coastal communities in Indonesia. Gender indeed emerged as significantly explaining plastic knowledge. Accordingly, men had a greater understanding than females; this was may because men were more likely than females to think about ways to solve the problem of microplastics (Phelan et al., 2020). It is possible that men's increased engagement with the problem of microplastics reflects a greater degree of MM complexity. Men may possess a better understanding of the interconnectivity of various concepts, which in turn, could empower them to generate more thorough solutions (Tjosvold, 2008; Hockerts, 2015).

The effect of gender on MM complexity remains ambiguous. Prior research concluded that women are more concerned about environmental threats (Pearson et al., 2017; Ballew et al.) and it is assumed that this female concern incentives women to seek information to enlarge their MM complexity. On the other hand, research suggests that men may have more climate change knowledge (Ballew et al., 2018) and knowledge of environmental pollution (Phelan et al., 2020). It is also assumed that this male greater knowledge results in a more complex MM allowing to identify more concepts and causal relations related to climate change.

While some studies suggest gender-based complexity differences of climate change MM (Pearson et al., 2017; Ballew et al., 2018; Phelan et al., 2020), other research has found no significant differences between genders. For example, a study examining differences in the perception of climate change among communities in Benin, West Africa aimed to gain insight into how local people experience climate change. The study found that gender was not a significant factor in explaining climate change perceptions. Similarly, Boissiere et al. (2013) found that gender was not a significant predictor of perceived consequences of climate change impacting tropical forests in Papua, Indonesia.

As there is no prior research on differences in MM complexity of climate change between genders in Africa, and literature is ambiguous regarding whether men or women hold more complex MM, the current study aims to contribute to the academic literature by providing empirical evidence regarding gender-based differences in MM complexity of climate change.

Thus it is hypothesized:

H_2: *Gender* significantly explains a difference in mental model complexity.

2.6 Climate change risk perception and mental model complexity

Risk perception represents whether an individual believes they are at risk of danger or harm during an event (Spence et al., 2012; Trope and Liberman, 2010; Brügger et al., 2015). Individuals who perceive climate change as an immediate threat reported higher risk perceptions (Spence et al., 2012). Risk perceptions are essential to understand because they underlie willingness to act on climate change (Spence et al., 2012). Moreover, when climate change is perceived as a distant event, it results in a more abstract representation (McDonald et al., 2015). This remote “big picture” is expected to be less detailed, leading to fewer causal relations and simplified causes and consequences of climate change: thus, less complex MM. To illustrate, when a region is at flooding risk, this may lead to memories of evacuating family members from flooded houses, illustrating a high perceived risk composed of detailed thinking (Trope and Liberman, 2010).

However, attempting to foresee a flood that has not been experienced before leads to greater difficulties in constructing a causal model to mitigate the event (Brügger et al., 2015; Liberman et al., 2002). Thereby, the closer the psychological distance to the problem is, the more coherent and consistent the MM related to the problem are likely to be (Bostrom, 2017). People who reported a higher level of risk perception may feel the need to understand the climate change event in greater detail, leading to the construction of a more complex MM (Barnes, 2019). It is expected that people perceiving climate change as a nearby event experience heightened levels of risk perceptions (Chu & Yang, 2020). The heightened risk perception may increase people's willingness to process information, resulting in more complex MM (Barnes, 2019). Thus, a higher perception of risk is expected to explain more complexity in MM.

H_3: *A higher level of climate change risk perceptions* explains more complexity in mental models.

2.7 Confounding variables explaining mental model complexity

Confounding variables can occur when there is a third variable that is causing the observed relationship between the two variables being studied (Bryman, 2012). To minimize the threat that other variables than the aforementioned predictor variables *gender and risk perception* may explain significant differences in MM complexity, this section will assess potential confounding variables alternatively explaining the effect on MM complexity.

2.7.1 Age

Because individuals build their MM based on a series of diverse experiences (Denzin & North, 1992), it is imaginable that older-aged respondents hold more complex MM than younger ones. On the other hand, since climate change is a relatively new issue (Stern, Dietz, Kalof & Guagnano, 1995), older aged people may not fully understand climate change's causes and consequences. Therefore, they may have a less complex MM of climate change than younger people who have grown up more aware of climate change risks (Spence et al., 2012; Trope and Liberman, 2010).

2.7.2 Education

Formal education provides individuals with the knowledge and skills, for example, system-thinking capabilities to understand complex issues such as climate change **(**Calori et al., 1994). It can be expected that individuals with higher levels of education would possess a more complex MM of climate change, their system-thinking capabilities would allow them to identify more complex causal relationships, compared to those with lower levels of education. Moreover, education is expected to be a confounded variable for independent variable gender. For example, women in developing countries may have less access to education and climate change resources (Bäthge, 2010) which can result in a less complex MM compared to men.

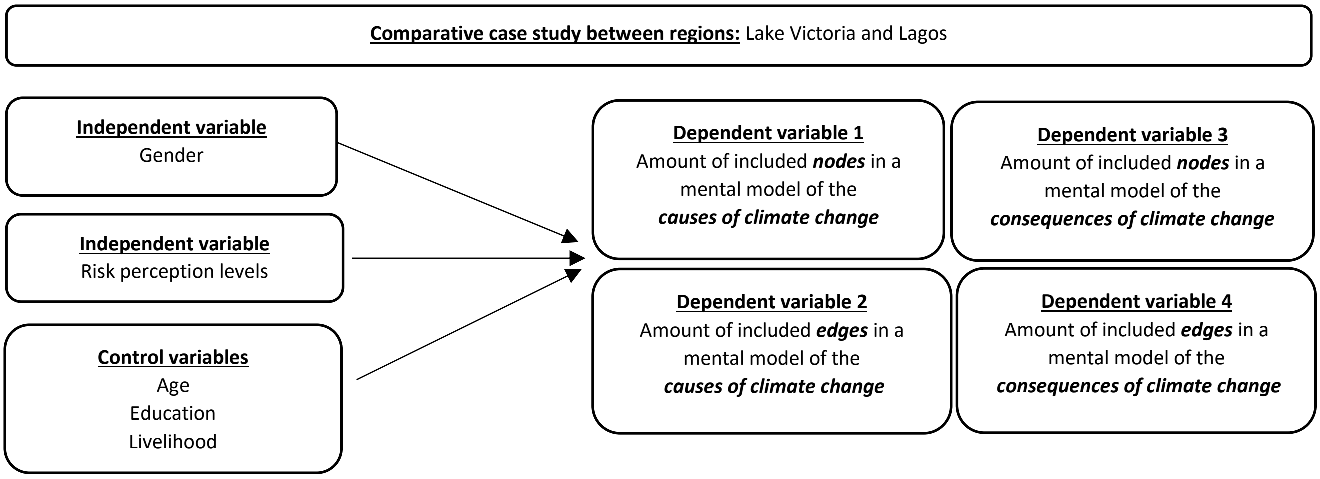
2.7.3 Livelihood

Prior research (Richert et al., 2016) suggests that individuals in scientific professions may have a more complex MM of climate change than individuals in non-scientific professions. This is potentially explained since individuals in scientific professions are more likely to have more advanced system-thinking capabilities necessary to understand complex interrelated circumstances and thus can generate a more complex MM compared to non-scientists (Calori et al., 1994; Richert et al., 2016). Also, different professions have altered levels of exposure to information and resources regarding climate change, thus leading to variations in MM (Driver & Streufert, 1969; Tjosvold, 2008). To conclude, the aforementioned confounding variables may alternatively explain the relationship between independent variables and MM complexity and will thus be controlled for during the analysis.

The framework *(figure 2)* summarizes the predictors potentially explaining variation in MM complexity of the causes and consequences of climate change.

Figure 2

Predictors of Differences in Mental Model Complexity



3. Methodology

3.1 Research design

To examine the MM of climate change and test raised hypotheses derived from the aforementioned theoretical framework, this thesis adopts a quantitative approach. The main reason for selecting a quantitative research methodology is that the quantitative approach allows for statistical analyses of a large population (Bryman, 2012), thereby the approach is useful for identifying statistical relationships between MM complexity and potential predictors. This thesis study does not examine MM through a qualitative research methodology since this method is more suitable for a smaller population. Moreover, the lack of numerical data during a qualitative research design to identify patterns threats the subjectivity during the data interpretation phase (Bryman, 2012). A noteworthy limitation of quantitative assessment of MM is that it often relies on pre-determined variables to enhance comparability across larger samples (van den Broek et al., 2021), however, this pre-selection limits the inclusion of alternative climate change causes and consequences to the cognitive model.

To examine the quantitative relationship between MM complexity and potential predictors, a correlational research design is applied which involves numerical measurement of variables and investigation of whether the variables correlate (Bryman, 2012). However since the research is non-experimental, thus no variable is manipulated, the statistical results solely determine a relationship between variables and no causality. A final threat to the correlation research design is the existence of confounding variables occurring when there is a third variable that is causing the observed relationship between the two variables being studied (Bryman, 2012). To minimize the threat that other variables than the aforementioned predictors may explain significant differences in MM complexity, this study controlled for potential confounding variables *age, education, and livelihood* during the statistical analysis.

3.2 Participants

This section reflects on the sampling procedure and characteristics. The student did not collect data to answer raised research questions: Dr. Karlijn van den Broek, co-lead of the MECCA project, provided access to the gathered data in Qualtrics and Excel for analytical purposes.

3.2.1 Sampling method

The data was collected between September and October 2022 in villages in the Lake Victoria region and Lagos. Per interview, 60 minutes were scheduled, and participants were financially compensated. Participants have been informed that their responses will remain anonymous and confidential. The local research institutions were tasked to develop a list of potential towns to conduct the surveys. The researchers employed two sampling strategies. First, a simple random probability strategy was used to randomly select 10 villages from the established list of potential towns. Second, a quota non-probability sampling was used to recruit participants within the sampled villages, ensuring a representative sample of the population.

In the Lake Victoria region, the total quota was established at 200 participants per country *(Tanzania, Uganda, Kenya)* and consists of four subgroup quotas: 160 community members, 30 local authorities and policy implementers, 5 climate change scientists, and 5 policymakers. In Lagos, the quota consisted of a minimum of 500 participants. A non-probability quota sampling strategy was thus utilized to select participants from a list of randomly selected villages. The objective was to obtain a sample that reflected the population in relative proportions of participants in different categories (Bryman, 2012). Within the current study, in Lake Victoria those participants were selected based on their livelihoods, such as fishing or policy makers. In Lagos, the quota consisted of a minimum number of participants.

3.2.2 Sample characteristics

The survey completion rate is 100% in Lake Victoria (N= 642) and 94,4% in Lagos (N= 352). The data collected from participants in Tanzania, Uganda, and Kenya were combined to represent the Lake Victoria region. As shown in Table 1, the sample distribution was almost equal across the three countries (N=222 in Tanzania; N=209 in Uganda; N=211 in Kenya). Thus, no country within the Lake Victoria region is oversampled, which could have skewed the region's representation. The tables in Appendix C reveal concerning the demographic distribution that the Lake Victoria sample had a higher proportion of men than women (73% vs. 27%). On the other hand, the gender balance was more even in Lagos, with 51% male and 49% female. Moreover, the Lake Victoria sample had a mean age ($\bar{x}$) of 35 years, which is seven years younger than the Lagos sample ($\bar{x}$=42). Lastly, the variability in livelihoods of the participants sampled in both regions necessitated the creation of new categories to accurately classify them. This was due to the differing approaches taken by data entry researchers in Lake Victoria and Lagos. While the former allowed participants to choose from eight pre-defined categories to classify their livelihoods, the latter recorded the full profession reported by the participants. This led to a wider range of livelihoods in Lagos. In order to facilitate comparison in the current study, the livelihoods of participants in Lagos were recoded into newly established categories. However, these new categories could not match with the pre-defined categories in Lake Victoria.

Table 1

Sampling Distribution within study regions Lake Victoria and Lagos: Amount of Participants and Livelihood

Amount of participants					
Region (Lake Victoria)	N	%	Region (Lagos)	N	%
Tanzania	222	34,5%	**Lagos**	352	100%
Uganda	209	32.5%			
Kenya	211	33%			
Total	642	100%	**Total**	352	100%

N = sample size

3.3 Instruments and materials

This section reflects on whether M-tool is a valid measurement by comparing the tool with several other instruments. The subsequent sections introduces the M-Tool and questionnaire procedure in current research to elicit MM.

3.3.1 M-Tool comparison with other instruments

There is a variety of methods available to elicit MM, namely fuzzy cognitive maps (Özesmi & Özesmi, 2004), Bayesian belief networks (Pollino, Woodberry, Nicholson, Korb, & Hart, 2007), cognitive maps (Axelrod 1976 ; Jones et al., 2014) and influence diagrams (Diffenbach, 1982). These methods have proven successful in producing MM insights on various topics (Gray et al., 2014; Wood et al., 2017). However, these methods have not been designed to assess MM of low illiteracy samples (van den Broek et al., 2021). For current study, the M-tool was employed by the researchers to elicit MM due to its capability to systematically compare MM across groups, which allowed for the identification of differences in MM complexity. To ensure the validity of the measurements, a pilot study was conducted in Tanzania using the M-Tool. The pilot participants were selected to be representative of the general population in Tanzania. Moreover, as the geographical regions in this case study exhibit high illiteracy rates (T*anzania 18%; Uganda 21%; Kenya 18%; Nigeria 23%*, Statista, 2021), the use of a predetermined set of pictograms as system components enables the elicitation of MM while not excluding groups with low literacy levels. This is because pictograms are visual symbols that can be universally understood, regardless of literacy proficiency. Thus, even individuals with low literacy levels can draw their understanding of the causes and consequences of climate change through the use of M-Tool.

3.4 Procedure

3.4.1 Identifying climate change concepts through a pilot study

The pilot participants were questioned in a survey about causes and consequences of climate change. Then, the researchers separately selected for Lake Victoria and Lagos the most frequently mentioned sixteen variables as climate change concepts. The participants can drag these concepts to the mapping screen and place arrows to indicate a relation and the relational strength between concepts. The arrow weights are coded from 1 to 3, where 1 represents the thinnest arrow and 3 the thickest arrow. The most frequently mentioned climate change causes and consequences varied notably between the two regions. As a result, two separate sets of pre-selected climate change concepts were developed, one for Lake Victoria and one for Lagos (table 2). Those descriptive concepts are subsequently visualized through pictograms (figure 3) that could be chosen to draw the MM in M-Tool.

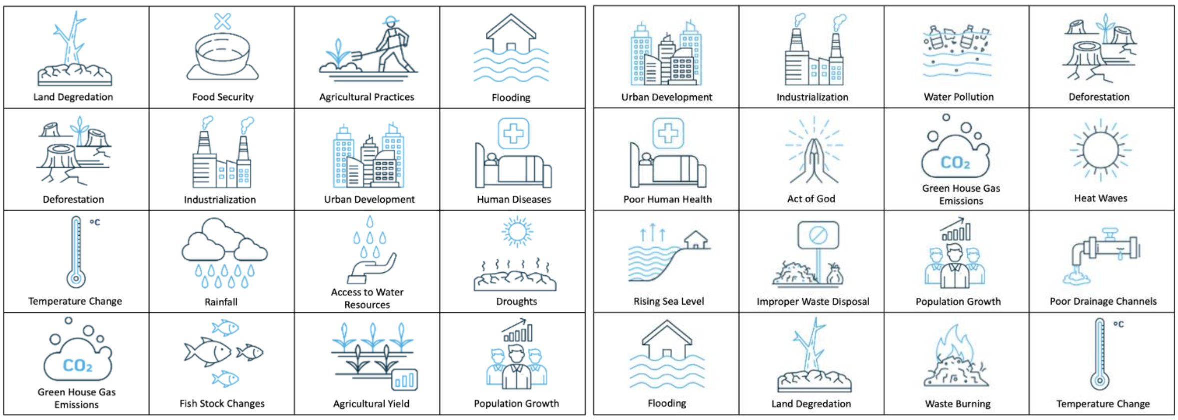
Table 2

Descriptive Climate Change concepts for Lake Victoria (upper table) and Lagos (lower table)

Lake Victoria: Climate change concepts			
1	Land degradation	**9**	Agricultural practices
2	Deforestation	**10**	Urban development
3	Temperature change	**11**	Access to water resources
4	Greenhouse gas emissions	**12**	Agricultural yield
5	Food security	**13**	Flooding
6	Industrialisation	**14**	Poor human health
7	Rainfall	**15**	Droughts
8	Fish stock changes	**16**	Population growth
Lagos: Climate change concepts			
1	Urban development	**9**	Heatwaves
2	Deforestation	**10**	Population growth
3	Greenhouse gas emissions	**11**	Land degradation
4	Improper waste disposal	**12**	Water pollution
5	Flooding	**13**	Act of god
6	Temperature change	**14**	Rising sea level
7	Industrialisation	**15**	Poor drainage channels
8	Poor human health	**16**	Waste burning

Figure 3

Climate Change concepts as Pictograms (set for Lake Victoria left, set for Lagos right)



3.4.2 Mapping mental models in M-Tool

M-tool is software to elicit MM and can be freely used through a mobile- or web application, which can be derived from www.m-tool.org (van den Broek et al., 2021). The standardized M-Tool software allows researchers to customize the tool by uploading video and audio material.

At the beginning of the actual study, participants were asked to confirm their informed consent for their data to be used for scientific purposes, such as presentations at academic conferences or publications in scientific journals, based on the elicited MM and questionnaire. Participants' identities were kept anonymous, and no data that could identify an individual was collected. Then, participants were provided with a video with instructions for the practice task. Before the participant could continue to the actual study, the practice task should be finished, which consisted of replicating a simple MM, ensuring familiarization with the software (*figure 4*). Secondly, the variables that can be used to draw the MM are explained in a video. Lastly, the mapping screen would show where participants could draw their MM. During the first mapping phase, participants were instructed to draw a MM that illustrates their understanding of the causes contributing to climate change. Then, participants were presented with a second mapping screen, where they could similarly map out their understanding of the consequences of climate change. Through the use of weighted arrows, participants were able to represent the relationships between their selected concepts within each of their maps. As a result, each participant generated two MM, with the exception of the practice task.

Figure 5 displays the described mental mapping procedure. The data output, such as the number of concepts and relationships, were exported to R-Studio for statistical analysis.

Figure 4

Practice Task M-Tool

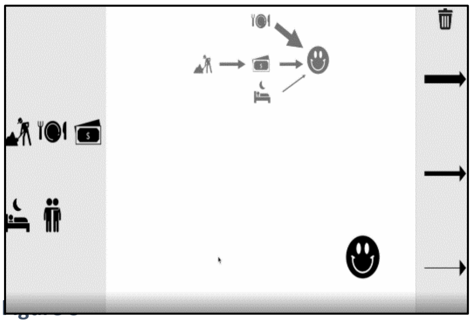
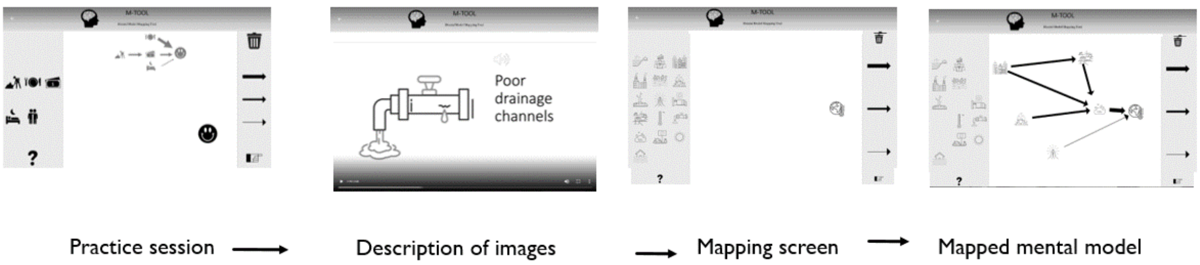


Figure 5

M-Tool Mental Mapping Procedure



3.4.3 Questionnaire procedure

After the MM is elicited through M-Tool, participants have been directed to Qualtrics for a questionnaire *(Appendix A)*. The level of perceived risk was measured through the questions in table 3. Lastly, the variable *gender* and control variable *age* were collected through additional demographic questions. Gender was measured through the question *'what is your gender?'* with answer options *'male/female/prefer not to say.'* Age was measured through the question *'what is your age (in years)?'* with open numeric answer options.

Table 3

Questions measuring Risk Perception Levels

Level of risk perception	
Question	**Answer options**
How serious a threat is climate change to the following: 1) You personally? 2) The people in this region? 3) Humanity as a whole? 4) The natural environment	5- point Likert scale *(No serious threat at all, Somewhat serious threat, Moderate threat, Serious threat, Very serious threat)*
How likely do you think it is that you will personally be harmed by climate change in your lifetime?	5- point Likert scale *(Very unlikely, Unlikely, Neither likely nor unlikely, Likely, Very likely)*
How likely do you think it is that people in this region will be harmed by climate change within your lifetime?	5- point Likert scale *(Very unlikely, Unlikely, Neither likely nor unlikely, Likely, Very likely)*

The questionnaire answers for "*what is your gender*" have been coded as 0= male, 1=female, 2=prefer not to say. Measures for the variable region have been derived from the location where the participant filled in the survey *(lake Victoria or Lagos)* and recoded as dummy-variable 0= Lake Victoria and 1= Lagos. Risk perception questions *(table 3)* have been measured through the average numerical value. The average value is calculated by first recoding the answer options to numerical values: whereas "no serious threat at all" and "very unlikely" correspond with the lowest perceived risk (*coded as '0').* The outer answer range "very serious threat and very likely" are coded as 4, indicating the highest perceived risk. The answers to the six risk perception questions have been summed; this cumulative total was divided by six to interpret the average risk perception level. When combining risk perception survey questions into a single index, it is important to confirm the high internal consistency between individual scale items. This ensures that each item is measuring the same underlying construct and that the index is a reliable measure of the concept being studied (Streiner, 2010). To check whether there is a high internal consistency between the individual scale items, Cronbach's Alpha was measured. A cut-off value of 0.7 for alpha was used to ensure internal consistency. The measured alpha coefficient was 0.78, so it is demonstrated that the scale items are related enough to be combined into one index to measure risk perception (Streiner, 2010).

The questionnaire measured additional constructs that are not analysed in this study. These constructs include the level of concern about climate change, the priority of concepts and strategies to address it, the stakeholder responsible for implementing mitigation strategies, the confidence in various stakeholders to mitigate climate change, and the media sources that respondents consult to gather information about climate change. The ongoing of current study solely addresses the questions that are relevant to the hypotheses.

3.4.4 Data cleaning process

A script freely available from m-tool.org was used to eliminate observations consisting of missing data in the elicited MM columns 'From,' 'To,' and 'User_ID.' The cleaned MM data was then saved in a new data frame, excluding participants who did not complete their MM. Duplicated rows from the User_ID column were removed from the dataset, leaving only one row for each participant. The original datasets contained duplicated rows since the initial data consisted of one row per identified causal relation per participant. This data was not required as the average amount of nodes and edges in a person's MM had already been calculated using the freely available script. Removing duplicated rows enabled the causes of climate change to be horizontally merged with the consequences of climate change in a new data frame based on the User_ID. For instance, in Lagos, the original data for the causes of climate change contained 2807 observations and 2161 observations for the consequences of climate change. After removing the duplicated rows, 274 observations remained in Lagos.

In order to conduct statistical analysis with the independent variables obtained from the questionnaire, several data-cleaning steps had to be performed. These steps included identifying and correcting any missing or incorrect data. For the "Gender" variable, any rows with missing data from non-response or containing a value of "3" or "4" were excluded. These values likely resulted from either selecting "other" as a response option (3) or were the result of a data-entry error (4). The number of participants who answered "other" to this question was minimal and could not reflect in a generalizable third category for gender.

With respect to the variable 'Age,' data points with age values below 18 were excluded from the dataset by recoding them to 'NA,' indicating a missing value that would subsequently be deleted. Children and teenagers were not included in the sample for the current study, which means that a small number of participants may have made a typographical error resulting in ages such as 5 and 13. In regards to the 'Livelihood' variable in Lake Victoria, it was discovered that values 7 and 6 had been incorrectly assigned. This was due to a lack of correspondence between the pre-established categories and data-entry. Specifically, category 6 was meant to represent scientists, while category 7 was meant to represent policy makers. These values were reversed in the provided data. In Lake Victoria, the variable "Education" was modified to align with pre-established categories. To achieve this, any value of 0 (no education) was replaced with a value of 1 (incomplete primary). The cleaned MM data was subsequently horizontally merged with the cleaned questionnaire data.

The cleaned data enabled the application of the paired-samples t-test and multiple linear regression to address research questions and hypotheses. The statistical procedures will be explained in the following section.

3.5 Statistical procedure

3.5.1 Analysing mental models

The data collected in M-Tool and Qualtrics was analysed using the statistical software R Studio: data was directly imported through a downloadable CSV file. To answer the first research question, *'What do the MM of the causes and consequences of climate change in Lagos and Lake Victoria look like?'* a prewritten script allow for visualization of the MM in RStudio (Boxtel & van den Broek, 2021). The parameters and content of the MM have been calculated per region. Those parameters included: 1) mean number of connections and 2) mean number of concepts. Lastly, the top five most connected concepts was analysed.

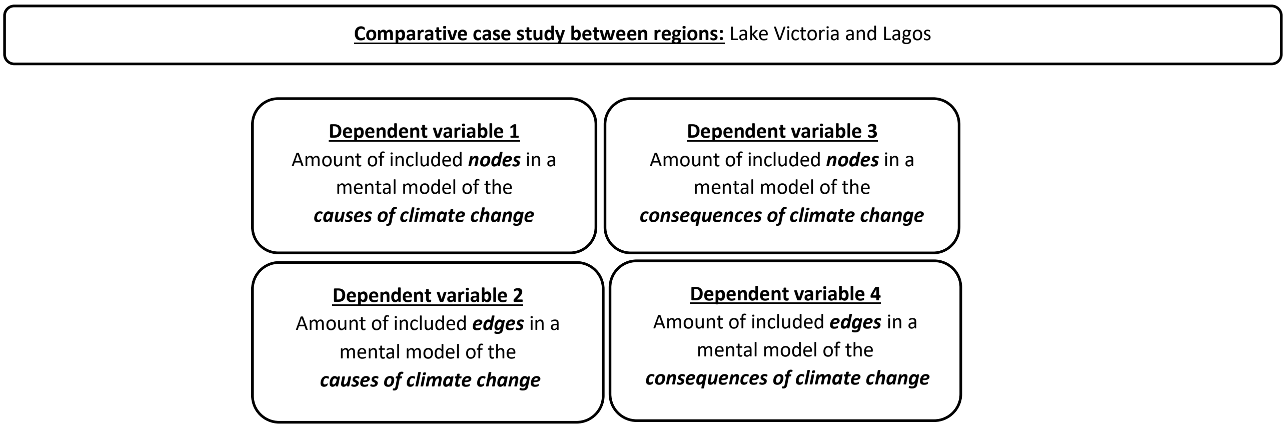
3.5.2 Statistical procedure

3.5.2.1 Dependent variables

Data was analysed through a network analysis approach (Newman, 2010). To measure the construct complexity, the prediction model would contain two structural parameters: 1) 'nodes' reflected how many of the sixteen pre-selected concepts *(table 3/figure 5)* were included in the MM, and 2) 'edges' reflected the mean number of weighted arrows per concept in the model for each participant. The complexity has been analysed for both MM complexity of climate change causes and consequences. To achieve this, the multiple linear regressions (MLR) are individually performed for both Lake Victoria and Lagos. Thus, four regression analyses have been conducted separately for both regions, thereby in total eight regression analysis *(figure 6).*

Figure 6

Four Dependent Variables to assess Mental Model Complexity differences of the Causes and Consequences of Climate Change



3.5.2.2 Independent variables

The independent variables included *gender and risk perception*. Moreover, control variables *age, education, and livelihood* were added to the model.

3.5.2.3 Hypothesis testing

This study allowed to answer formulated research questions according to the following hypothesis:

H_1: Mental models of climate change consequences consist of more concepts than mental models of climate change causes
H_2: Gender significantly explains a difference in mental model complexity
H_3: A higher level of climate change risk perceptions is associated with more complexity in mental models; thus, a positive relationship exists between risk perception and mental model complexity

When the resulting P-value was smaller than the defined significance level of 5%, the null hypothesis were rejected and the alternative hypothesis supported. The results of a paired sample T-test answered H_1. Lastly, the results of the multiple linear regression would indicate an answer on H_2 and H_3.

3.5.2.4 Paired T-Test: Assumptions and data transformation

A paired T-Test was applied to understand whether MM of climate change consequences consist of more concepts than MM of climate causes. Before performing the paired T-test, 1) the assumption of normality and 2) the assumption of equal variance needed to be checked (Hsu & Lachenbruch, 2014). The MM complexity parameters between the two paired groups should be normally distributed to meet the normality assumption (Schmidt & Finan, 2018). The statistical test Shapiro-Wilk was too stringent for the large sample size (Jurečková & Picek, 2007); thus, visual inspection through a histogram and Q-Q plot was the appropriate method to test the normality assumption (Das, 2016). For most groups, the data was left skewed, and thereby the assumption of normality was initially not met. To transform the data, a logarithmic data transformation was applied (Feng et al., 2014). However, even after a logarithmic data transformation, the assumption of normality was not met for the T-test evaluating the amount of included nodes in the MM of the causes of climate change compared to the consequences. The normality assumption was also not met after data transformation for the amount of included edges in the MM of climate change causes compared to consequences in Lagos (Appendix D.1). When the data was not normally distributed, a non-parametric test was applied instead of the paired samples T-Test. The non-parametric Wilcoxon paired T-Test was subsequently the appropriate statistical test to determine MM complexity differences between the causes and consequences of climate change (Wiedermann & Eye, 2013).

To test the second assumption of equal variance, Levene's statistical test determined whether the variance of the MM of the causes and consequences of climate change were statistically different. When the derived P-value from the test was greater than the significance level of 0.05, it was assumed that the variances were equal and that the assumption of equal variance was met. When the assumption was not met, Welch's paired T-Test was the appropriate statistical test since the test did not assume that the variances between the two groups compared are equal. The assumption of equal variance was not met for the amount of included nodes and edges in Lake Victoria and the amount of included edges in Lagos comparing MM of the causes of climate change with the consequences (Appendix D.1 and D.2). When both the assumptions of normality and equal variance were violated, the non-parametric Wilcoxon test was applied.

3.5.2.5 Multiple linear regression: Assumptions and data transformation

The results of the multiple linear regression (MLR) model predicted the relationship between *gender*, *risk perception*, and *MM complexity*. Prior to performing the MLR analysis, four statistical assumptions needed to be met: 1) the assumption of linearity, indicating that there must be a linear relationship between the dependent and independent variables, 2) the assumption of normal distribution, indicating that the residuals (the differences between the observed values and the predicted values*)* shall be normally distributed, 3) the assumption of homoscedasticity shall be met, and finally, 4) there must be no multicollinearity or no instability of the regression coefficients (Osbourne & Waters, 2002).

Those four assumptions have been tested as follows: First, to test the linearity, a scatter plot of the predicting and control variables was created against the dependent variables. Accordingly, if there did not occur an apparent curvature, fan shape, or strong curve in the patterns or other deviations from linearity, the assumption of linearity was met (Osbourne & Waters, 2002). Secondly, since the Shapiro-Wilk test was overly sensitive to detect minor deviations from normality in current studies' large sample size (Ahad et al., 2011), this frequently led to rejecting the normality assumption, even when the deviation from normality was insignificant. Thus, applying a graphic approach to evaluate the normality assumption was more appropriate (Ghasemi & Zahediasl, 2012). Thus, a graphical approach was conducted by visualizing a histogram and observing whether the histogram was bell-shaped with only one peak and symmetric around the mean, thus normally distributed. Also, a Q-Q plot was visualized to test the normal distribution: if the data points were plotted on a straight line, the data was considered sufficiently close to normally distributed. Thirdly, the assumption of homoscedasticity is visually inspected since the Breusch-Pagan test was less likely to detect violations of homoscedasticity at larger sample sizes (Breusch & Pagan, 1979). The residuals were plotted against the predicted values; if the pattern suggested a random scattering, the assumption of homoscedasticity was met. Thus, if there is limited variance or substantial inconsistency across the scattering, the assumption of homoscedasticity is violated (Breusch & Pagan, 1979). Lastly, no multicollinearity should exist (Siegel, 2016), meaning two or more predictors strongly correlate. The variance inflation factor (VIF) was calculated to measure the degree to which the variance of the estimated coefficients increased due to multicollinearity. A value smaller than 5 indicates no significant multicollinearity, thereby meeting the assumption (Akinwande et al., 2015).

The multiple linear regression analysis could be performed when the assumptions were met. However, the assumption of normality was not met for the multiple regression model consisting of the dependent variable amount of included edges in a MM of the consequences of climate change in Lagos (Appendix E.8). The residuals were skewed to the left; therefore, a logarithmic data transformation was applied to meet the assumptions. To do this, RStudio was prompted to calculate the natural logarithm of the data points.

3.6 Ethical issues

All participants provided informed consent for their data to be used for scientific purposes, such as presentations at academic conferences or publications in scientific journals, based on the elicited MM and questionnaire. No data that could identify an individual was collected. Survey data is stored at XM Qualtrics Survey cloud, and M-Tool data is stored on the server of Heidelberg University, thereby cohering with the General Data Protection Regulation (GDPR) regulations. After the data was transferred for analytical purposes, the researcher stored the data on the laptop’s hard disk. The following has been agreed upon by researcher Charlotte van Hal:

I will keep all the research information shared confidential;

I will immediately inform supervisor of any potential data breaches so that she can promptly address the situation.

4. Results

This chapter reports on the findings of the MM of climate change causes and consequences in Lake Victoria and Lagos. The descriptive statistics of the dependent and explanatory independent variables are presented in appendixes B and C. Before performing a statistical T-test and multiple linear regression, the aforementioned assumptions should be tested (Howell, 1982). Appendix D investigated for the statistical t-tests whether the variables are normally distributed and whether the assumption of equal variance is met. Appendix E displays the assumptions that should be met to perform a multiple linear regression.

4.1 Mental models of climate change causes and consequences

To answer the first research question, "W*hat do the MM of the causes and consequences of climate change in Lake Victoria and Lagos look like?"* the 1) average number of concepts (nodes), 2) average number of causal relations (edges), and the 3) most connected concepts were calculated, indicating connections frequently mentioned by participants. Lastly, the percentage (%) of the identified relationship relative to all identified relationships in the groups MM was calculated. To illustrate, 14.2% of individuals in Lagos attributed greenhouse gas emissions as a cause of climate change in their MM (Table 4). The MM that has been aggregated are represented through pictograms that illustrate concepts, as shown in figure 7. The meaning of these pictograms are clarified in figure 3. Alternatively, a version of the aggregated mental models with written instead of visual concepts can be found in Appendixes F to I.

Table 4

Mental Models of Climate Change: Top five perceived Causes and Consequences of Climate Change

	Lake Victoria		Lagos	
	Climate change causes	**Climate change consequences**	**Climate change causes**	**Climate change consequences**
Top 5 perceived causes and consequences of climate change *and the percentage (%) of the identified relationship relative to all identified relationships in the groups MM*	1) Deforestation – climate change *(10.3%)* 2) Droughts – climate change *(6.5%)* 3) Industrialization – climate change *(5.5%)* 4) Land degradation – climate change *(5.1%)* 5) Rainfall – climate change *(4.9%)*	1) Climate change – droughts *(9.1%)* 2) Climate change – food security *(5.9%)* 3) Climate change – rainfall *(5.8%)* 4) Climate change – fish stock changes *(5.2%)* 5) Climate change – flooding *(4.8%)*	1) Greenhouse gas emissions – climate change *(14.2%)* 2) Industrialization – climate change *(12.2%)* 3) Population growth – climate change *(9.3%)* 4) Urban development – climate change *(7.8%)* 5) Waste burning – climate change *(7.3%)*	1) Climate change – temperature change *(12.6%)* 2) Climate change – flooding *(12.3%)* 3) Climate change – heatwaves *(11.3%)* 4) Climate change – rising sea level *(10.6%)* 5) Climate change – land degradation *(8.4%)*

M = mean, SD = standard deviation

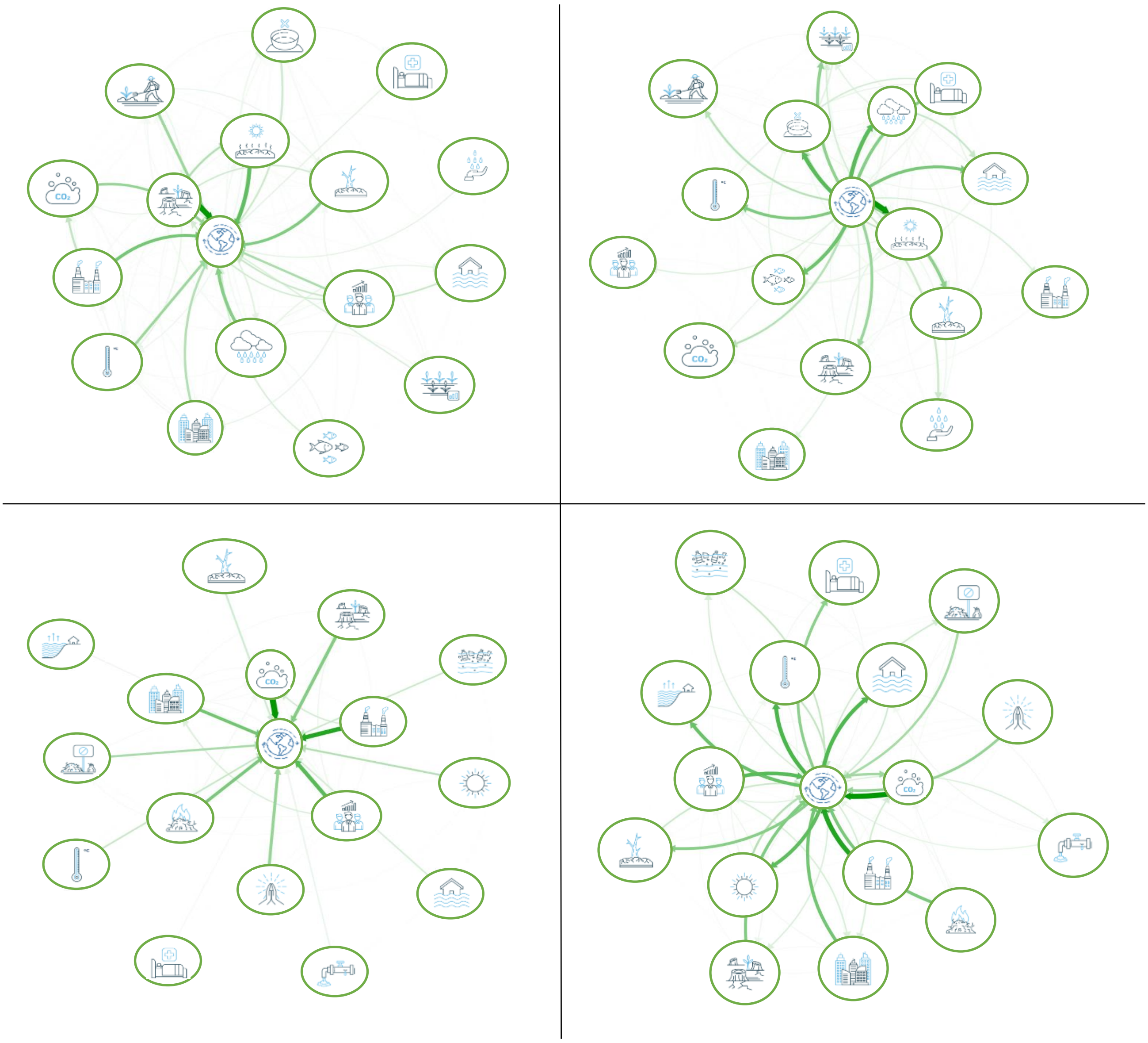
People in Lake Victoria and Lagos both identified *industrialization* as one of the top five factors that contribute to climate change. On the contrary, whereas people in Lake Victoria perceive additionally *deforestation, drought, land degradation, and rainfall* as important causes of climate change, people in Lagos perceive additionally *greenhouse gas emissions, population growth, urban development, and waste burning* as primary causes of climate change.

Looking at the descriptive statistics of climate change consequences, the people in Lake Victoria perceive drought as the primary consequence of climate change. In contrast, citizens of Lagos perceive temperature change as the most important consequence of climate change. Both regions agree that *flooding* is among the most perceived consequences of climate change. People in Lake Victoria included *food security* and *fish stock changes* as important consequences, whereas people in Lagos included *heatwaves*, *rising sea levels* and *land degradation* as consequences of climate change.

Figure 7

Aggregated Mental Models of Climate Change

Left corner: Change Causes –Lake Victoria
Right corner: Climate Change Consequences –Lake Victoria
Left bottom: Change Causes –Lagos
Right bottom: Climate Change Consequences –Lagos



4.1.1 Mental model complexity of climate change comparing consequences with causes

The purpose of this section is to evaluate the differences in MM complexity between the causes and consequences of climate change. To achieve this, a paired samples T-test was conducted to determine the statistical significance of the differences. The hypothesis will be independently tested for each region.

H_1: Mental models of climate change consequences consist of more concepts (nodes) than MM of climate change causes.

Amount of included nodes comparing mental models of climate change causes with consequences

For the structural parameter nodes, the results for Lake Victoria in table 5 illustrate that the mean number of included nodes of climate change consequences (M=10.8, SD=3.07) is higher than the mean number of included nodes in the mental models of the causes of climate change (M=7.47, SD=2.66). Derived from Welch's paired T-test results, this difference is statistically significant (t (532) = -71.924, p =<0.05). Thereby, H_1 is supported in Lake Victoria.

For the region Lagos, the results of paired samples T-test illustrate that the average amount of included nodes of the consequences of climate change are more complex for the parameter nodes (causes: M=5.89, SD=1.47, consequences: M=5.56, SD=1.14). The difference in average number of included nodes is statistically significant (t (249) =2.6614, p=<0.05). Thus, MM of the consequences of climate change in Lagos does consist of a higher mean amount of nodes than MM of the causes of climate change causes: H_1 is also supported in Lagos.

Table 5

Paired Sample T-Test Results: The Average number of Nodes in Mental Models of Climate Change Causes and Consequences.

Lake Victoria	Climate Change Causes		Climate Change Consequences		t	df	p
	M	SD	M	SD			
Average number of nodes	7.47	2.66	10.80	3.07	-71.924	532	< 0.05
Lagos	**Climate Change Causes**		**Climate Change Consequences**		**t**	**df**	**p**
	M	**SD**	**M**	**SD**			
Average number of nodes	5.56	1.14	5.89	1.47	2.6614	249	< 0.05

M = mean, SD = standard deviation
t = t-value, df = degrees of freedom, p = level of significance

Amount of included edges comparing mental models of climate change causes with consequences

Literature has been ambiguous about whether MM of the consequences of climate change also consists of a higher mean amount of edges (causal relations) than the causes of climate change. For the second structural parameter edges, the descriptives and results of the Welch's paired T-test for Lake Victoria illustrate that the average included causal relations of the consequences of climate change (M=17.1, SD=7.9) are higher than average included causal relations of the causes of climate change (M=9.27, SD=5.38). This difference is statistically significant(t (532) = -64.634, p=<0.05). Thus, the mean amount of included edges at MM of the consequences of climate change is significantly larger relative to the causes of climate change in Lake Victoria (table 6).

The results of the Wilcoxon paired T-test for Lagos illustrate that the average amount of included edges of the MM of consequences of climate change (M=7.94, SD=5.61) are less than average amount of included edges of the causes of climate change (M=10.32, SD=8.04). This difference is statistically significant (V (249) =15414, p=<0.05). Thus, contrary to the Lake Victoria region, in Lagos MM of the consequences of climate change do include on average fewer edges than MM of the causes of climate change.

Table 6

Paired Sample T-Test Results: The Average number of Edges in Mental Models of Climate Change Causes and Consequences.

Lake Victoria	**Climate Change Causes**		**Climate Change Consequences**		**t**	**df**	**p**
	M	**SD**	**M**	**SD**			
Average number of edges	9.27	5.38	17.1	7.9	-64.634	532	< 0.05
Lagos	**Climate Change Causes**		**Climate Change Consequences**		V	df	p
	M	**SD**	**M**	**SD**			
Average number of edges	10.32	8.04	7.94	5.61	15414	249	< 0.05

M = mean, SD = standard deviation
t = t-value, df = degrees of freedom, p = level of significance

4.2 Predicting differences in climate change mental model complexity

To answer the second and third research question regarding to which extent gender and risk perception predict MM complexity, four multiple linear regressions have been conducted independently for Lake Victoria and Lagos to compare differences in MM complexity of the causes and consequences of climate change. Current introductory section provides an overview of the suitability of the multiple regression models and subsequently presents the statistical findings for the predictors *gender* and *risk perception*. Lastly, the statistical results for the control variables *age*, *education*, and *livelihood* are presented.

The assumptions have been tested statistically before performing a multiple linear regression analysis. Appendix E presents the assumptions, which first consist of the assumption of linearity. Secondly, whether the residuals of the regression follow a normal distribution and if the assumption for homoscedasticity was met. Lastly, appendix E presents Pearson's correlation value for the independent variables that tested them for multicollinearity. The results of the assumptions tests concluded that all assumptions were not violated except the normal distribution for the regression model measuring variance in climate change consequences for the parameter edges in Lagos (appendix E.8): The original data was lefty skewed, harming the assumption of normality, this was improved through a logarithmic data transformation. Thus, after assessing the assumptions, multiple linear regression is the appropriate statistical test to predict MM complexity differences.

4.2.1 Multiple linear regression model: Predicting differences in mental model complexity of the causes of climate change

Table 7 presents the results of the multiple linear regression predicting differences in the mean amount of included nodes and edges in people's MM of climate change causes.

Table 7

Multiple Linear Regression results: Mental Models of the Causes of Climate Change

Climate change causes	Nodes (β)		Edges (β)	
	Lake Victoria	**Lagos**	**Lake Victoria**	**Lagos**
(Intercept)	7.291***	5.713***	7.564***	11.129*
Gender	-0.011*	-0.267	-0.590	0.199
Risk perception	0.028	0.284**	-0.171	0.023
Age	-0.022*	-0.016	-0.003	0.584
Education	0.238***	0.054	0.305**	0.685
Livelihood	0.036	-0.065	0.570***	-1.576
Adjusted R-squared	0.046	0.050	0.065	-0.005

**P<0.05, **P<0.01, ***P<-0.001*
β = bètacoëfficiënt

The multiple linear regression model in Lake Victoria predicted 4.6% of the variance on the mean amount of included nodes in a person's MM of the causes of climate change (R^2 =.046, F(5,520) = 6.064, p=<0.05). In Lagos, the multiple linear regression model predicted 5% of the variance on the mean amount of included nodes in a person's MM of the causes of climate change (R^2 =.050, F(5,239) = 3.558, p=<0.05).

For the structural parameter edges, the regressions model in Lake Victoria explains 6.5% of the variance on the average amount of included edges in a person's MM of the causes of climate change (R^2 =.065, F(5,520) = 8.351, p=<0.05). In Lagos, the multiple linear regression model predicted 0% of the variance on the average amount of included edges in a person's MM of the causes of climate change (R^2 = -0.005, F(5,239) = 0.777, p=>0.05).

Gender and mental model complexity of the causes of climate change

To provide insights into the relationship between gender and climate change MM complexity, H_2 was deduced from existing theory. H_2 states *that gender significantly explains a difference in MM complexity*. To interpret the differences between genders, the beta coefficients displayed in table 5 indicate the change in the mean amount of included nodes associated with a one-unit change in the independent variable, holding all other independent variables from the full regression model constant.

When looking at the results for explaining MM of the causes of climate change, three out of four beta coefficients are negative (nodes Lake Victoria β = -.011, t (532) = -0.041, $p < 0.05$; nodes Lagos β = -.027, t (249) = -1.571, $p > 0.05$; edges Lake Victoria β = -.590, t (532) = -1.147, $p > 0.05$), indicating that men tend to have more complex MM of the causes of climate change than women in Lake Victoria and in Lagos for the parameter nodes. However, in Lagos women include a higher average amount of edges in their MM of the causes of climate change (edges Lagos β = .207, t (249) = 0.199, $p > 0.05$). Solely the results demonstrating that men include a higher average amount of nodes in their MM of climate change causes in Lake Victoria are statistically significant.

Risk perception and mental model complexity of the causes of climate change

The final research question aimed to understand to which extent the perception of climate change risk predicts MM complexity. H_3 states that *a higher level of climate change risk perceptions is associated with more complexity in mental models; thus, a positive relationship exists between risk perception and mental model complexity.*

When interpreting the relation between risk perception and the MM complexity of the causes of climate change (table 6), risk perception appeared to be solely a significant predictor for variation in the amount of included nodes in Lagos (β = .284, t (249) = 2.622, $p <0.01$); this means that an increase in risk perception of one point on a 5-point Likert scale predicts a higher MM complexity through the inclusion of 0.284 additional nodes. There exists a weakly positive however nonsignificant relationship between risk perception and in Lake Victoria the average amount of included nodes at someone's MM (β = .028, t (532) = 0.143, $p > 0.05$), and in Lagos, a positive weak nonsignificant relationship on the average amount of included edges (β = .023, t (249) = 0.036 $p > 0.05$). Contrary to the raised hypothesis, the relationship between risk perception and the mean amount of included edges in someone's MM is weakly negative in Lake Victoria, however, nonsignificant (β = -0.171, t (532) = -0.431, $p > 0.05$).

4.2.2 Multiple linear regression model: Predicting differences in mental model complexity of the consequences of climate change

Table 8 presents the results of the multiple linear regression predicting differences in the mean amount of included nodes and edges in people's MM of climate change consequences.

Table 8

Multiple Linear Regression results: Mental Models of the Consequences of Climate Change

Climate change consequences	Nodes (β)		Edges (β)	
	Lake Victoria	Lagos	Lake Victoria	Lagos
(Intercept)	6.686***	3.143***	10.133***	4.552
Gender	0.309	0.074	-0.575	0.309
Risk perception	0.456*	0.245*	0.195	-0.025
Age	-0.016	0.001	-0.011	0.035
Education	0.476***	0.206***	0.812***	0.652
Livelihood	0.061	0.106	0.957***	0.045
Adjusted R-squared	0.136	0.067	0.123	0.016

**P<0.05, **P<0.01, ***P<-0.001*
β = bètacoëfficiënt

The multiple linear regression model in Lake Victoria predicted 13.6% of the variance on the mean amount of included nodes in a person's MM of the consequences of climate change (R^2 =.136, F(5,520) = 17.54, p=<0.05). In Lagos, the multiple linear regression model predicted 6.7% of the variance on the mean amount of included nodes in a person's MM of the consequences of climate change (R^2 =.067, F(5,239) = 4.512, p=<0.05). The statistical analysis of the regression model indicates an explanatory power of 12.3% for the variability of included edges in a person's MM of the consequences of climate change observed in Lake Victoria (R^2 =.123, F(5,520) = 15.76, p=<0.05). In Lagos, the multiple linear regression model predicts a marginal 1.6% variance on the average amount of included edges in a person's MM of the consequences of climate change (R^2 = .016, F(5,239) = 1.803, p=>0.05).

Gender and mental model complexity of the consequences of climate change

When evaluating gender differences in MM complexity of the consequences of climate change, it appears that, in contrast to the MM of the causes of climate change, three out of four beta coefficients are positive (nodes Lake Victoria β = .309, t (532) = 1.098, p > 0.05; nodes Lagos β = .074, t (249) = 0.436, p > 0.05; edges Lagos β = .309, t (249) = 0.425, p > 0.05). The positive directed beta coefficients indicate that women tend to have more complex MM in Lagos and Lake Victoria for the parameter nodes. For the parameter edges in Lake Victoria, man included a higher average amount of edges in their MM of the consequences of climate change (Lake Victoria β = -.575, t (532) = -0.778, p > 0.05). However, since all p-values indicating the effect of gender on MM complexity of the consequences of climate change are nonsignificant, H_2 *gender significantly explains a difference in MM complexity* is not supported: gender does not significantly predict variation in the mean amount of included edges in a person's MM of the consequences of climate change.

Risk perception and mental model complexity of the consequences of climate change

Looking at the relationship between risk perception and the MM complexity of the consequences of climate change (table 7), in Lagos, an increase in risk perception of one point on a 5-point Likert scale predicts a higher MM complexity through the inclusion of 0.245 additional nodes ($\beta=0.245$ $t(249) = 2.265$; $p=<0.05$). This relation is stronger in Lake Victoria, where an increase in risk perception predicts 0.456 additional nodes ($\beta=0.456$ $t(532) = 2.102$; $p=<0.05$). There exists a positive nonsignificant relation between the amount of edges in someone's MM of the consequences of climate change in Lake Victoria ($\beta=0.195$ $t(532) = 0.342$; $p=>0.05$) and a nonsignificant weak effect on the mean amount of included edges in Lagos ($\beta= -.245$ $t(249) = -0.055$; $p= > 0.05$).

4.2.3 Gender and risk perception predicting differences in the mental model complexity of the causes and consequences of climate change

When interpreting the gender differences, the regression results (tables 7 and 8) indicate that only male and female participants differ significantly with respect to the mean amount of included nodes in their MM of the causes of climate change in Lake Victoria. Thereby, H_2 *gender significantly explains a difference in MM complexity* is supported solely for the amount of included nodes for MM of the causes of climate change for people in Lake Victoria. Gender does not consistently predict variation in MM complexity of the causes of the consequences of climate change.

Moreover, H_3 stating that *a higher level of climate change risk perceptions is associated with more complexity in mental models; thus, a positive relationship exists between risk perception and mental model complexity* is supported in Lagos for the average amount of included nodes at MM of climate change causes and consequences and in Lake Victoria for the average amount of included nodes at MM of the consequences of climate change. The relationship between risk perception and the average amount of included edges is nonsignificant positive in Lake Victoria for MM of the consequences of climate change and in Lagos for the MM of the causes of climate change. Contrary to expected, the relationship between risk perception and MM complexity is weakly negative; however nonsignificant in Lake Victoria on the average amount of included edge of MM of climate change causes and in Lagos on the average amount of included edges of MM of the consequence of climate change.

5. Discussion

This research aimed to understand the perception of climate change causes and consequences, what explains a difference in mental model (MM) complexity, and how this regionally differs. To do so, the MM complexity was assessed in two African regions severely impacted by climate change: Lake Victoria and Lagos. The study was structured around three research questions and three hypotheses. The first research question investigated MM of climate change causes and consequences in Lake Victoria and Lagos. The second question addressed whether gender explains differences in MM complexity. The third question investigated whether risk perception levels explain differences in MM complexity.

5.1 Mental models of climate change causes and consequences

To answer the first research question, the mean number of included concepts, causal relations, and most connected concepts were calculated. H_1 stated that *mental models of climate change consequences consist of more concepts than MM of climate change causes.* The results of the study suggest that H_1 is supported in both Lake Victoria and Lagos.

Amount of included concepts

The results demonstrating that MM of climate change consequences include a higher amount of concepts than MM of climate change causes (H_1) aligns with the theory that people are more cognitively engaged with the consequences of climate change, as opposed to the causes, due to the impact of climate change on their daily lives (Wolf & Moser, 2011). Extreme weather events, such as severe droughts and flooding, can have devastating consequences for communities in Lake Victoria and Lagos (Müller et al., 2014). Consequently, people are expected to be more motivated to understand the consequences of climate change. This newly acquired information about the consequences is likely to lead to a greater amount of included concepts in a person's MM (Tjosvold, 2008; Hockerts, 2015), as demonstrated by the current study.

Moreover, people may believe they have greater control over the consequences of climate change than the causes. For example, people may consider taking actions to adapt to the consequences of climate change, such as exploring alternative economic activities when climate change threatens the longevity of one's livelihood or migrating to more fertile land. This feeling of control may further encourage people to seek out information about the consequences of climate change leading to a greater amount of included concepts in a person's MM (Tjosvold, 2008; Hockerts, 2015).

However, the finding suggesting that MM of the consequences of climate change are more complex than the causes contradicts the theory that most climate change consequences could be psychologically perceived as 'too far and distant' (McDonald et al., 2015; Trope and Liberman, 2010). Consequently, the distant perception would prevent understanding on a detailed level, leading to the inclusion of fewer concepts in a person's MM of climate change consequences compared to causes.

Amount of included causal relationships

This study expected a higher amount of included concepts in a person's MM of the consequences of climate change (H_1) compared to the causes of climate change. For explorative purposes, the differences in the amount of included causal relationships was tested. The results demonstrate that MM of the consequences of climate change include a higher amount of included concepts in both regions but does not include a higher amount of included causal relations in Lagos. The finding that there is no difference in the amount of included causal relations between a person's MM of the causes and consequences of climate change in Lake Victoria does align with the ambiguousness in literature (Axelrod et al., 1996; Barnes, 2019; McDonald et al., 2015; Trope and Liberman, 2010).

The finding that the amount of included causal relationships is not higher for the MM of climate change consequences than causes in Lagos contradicts the assumption that people are more cognitively engaged with the consequences of climate change, as opposed to the causes, due to the impact of climate change on their daily lives (Wolf & Moser, 2011). It was expected that people who experience the consequences of climate change on their daily life would be more motivated to understand the underlying causal relationships, leading to a better understanding of climate change (Tjosvold, 2008; Hockerts, 2015).

Comparison between the amount of included concepts and the amount of included causal relationships

As evidenced by the empirical results from H_1, people are able to include more concepts, such as the climate change impact on human health and agricultural yield, in their MM of the consequences of climate change than the causes. However, people in Lagos experience more challenges in understanding the causal relationships between the consequences of climate change. As evidenced by the explorative study results, people in Lagos are more likely to identify more causal relations of the causes of climate change but have a more challenging time in comprehensively understanding more specific consequences.

Mental model content differences

Lastly, the MM comparing Lake Victoria and Lagos experience content differences. Looking at the MM of climate change causes, the sole coherence between regions is the inclusion of industrialization as one of the top 5 perceived causes. People in Lake Victoria perceive *deforestation, drought, land degradation, and rainfall* as important causes of climate change. People in Lagos perceive *greenhouse gas emissions, population growth, urban development, and waste burning* as primary causes of climate change. People in both regions agree that *flooding* is among the top five consequences of climate change. People in Lake Victoria included *droughts, fish stock changes, rainfall,* and *food security* as important consequences, whereas people in Lagos included *temperature change, heatwaves, rising sea levels,* and *land degradation.* Those top five perceived climate change consequences between regions seem to overlap since rising sea levels and droughts directly result from rainfall, heat waves, and temperature changes. The difference in MM content of climate change causes seems possibly explained due to geographical differences. A review of the geographical contexts indicates that many households living near Lake Victoria have depended on fishing and farming for many generations (Geheb & Binns, 1997); this may make them more aware of the causes' impact on their agricultural livelihood. In contrast, Lagos is a highly urbanized region with a high population density (Molla et al., 2022; Aluko, 2011), making people potentially more aware of the impact of greenhouse gas emissions on their health. The observed regional differences in MM content align with the findings arguing that MM are established through experiences with a person’s surroundings (Jones et al., 2011).

5.2 Gender and climate change mental model complexity

To answer the second research question investigating differences in MM complexity explained through gender, H_2 was formulated, stating that *gender significantly explains a difference in mental model complexity*. The research did not find a consistent relationship between gender significantly explaining complexity differences in MM of climate change causes and consequences, except for the amount of included concepts in Lake Victoria for MM of climate change causes.

The absence of a consistent gender-based explanation for differences in MM complexity of the causes and consequences of climate change does not align with previous research by Phelan et al. (2020), demonstrating that gender may explained differences in climate change knowledge. The expectation was that increased knowledge would result in a better understanding of a system. As knowledge increased, it was expected that people would be able to identify causal connections between seemingly unrelated concepts of climate change, leading to a more comprehensive understanding of the complex system.

However, the lack of observed gender-difference coheres with studies by Sanchez et al. (2012) and Boissiere et al. (2013) concluding that gender was not significant explaining climate change perceptions among communities in Benin, West Africa and perceived consequences of climate change in Papua, Indonesia.

Solely the results demonstrating that men include a higher amount of concepts in their MM of climate change causes in Lagos is statistically significant. The conclusion that men include a higher amount of concepts in their MM of climate change causes can be explained through a study concluding that men in the United States have a better understanding of global warming than women (Ballew et al., 2018). This greater understanding could be caused since a study found that men are more likely than females to think about ways to solve environmental problems (Phelan et al., 2020). Those findings contrast with Pearson et al. (2017), concluding that women perceive climate change as a higher threat than men, it was assumed that female concern would incentivize females to seek information and subsequently enlarge their MM complexity.

To conclude, gender did not consistently explain the MM complexity of climate change causes and consequences, neither in Lake Victoria nor in Lagos, except for the amount of included concepts of MM of climate change causes in Lake Victoria.

5.3 Risk perception and climate change mental model complexity

The final research question investigated whether risk perception levels explain differences in MM complexity. H_3 stated that *a higher level of climate change risk perceptions explained a higher complexity in mental models.* The results indicated that people who perceived a higher climate change risk did not consistently tend to have a more complex MM.

However, a positive relationship existed between a greater perceived risk in Lagos, resulting in a higher amount of included concepts at the MM of the causes and consequences of climate change, and in Lake Victoria, a higher amount of included concepts at MM of the consequences of climate change. The conclusion that people with a higher climate change risk perception seem to include a higher amount of concepts in their MM is supported by literature arguing that people who reported a higher level of risk perception may feel the need to understand the climate change event in greater detail (Barnes, 2019; Trope and Liberman, 2010). A higher perceived risk was expected to lead to a more complex MM because people perceiving a higher risk level may feel a greater urgency to gather more information about climate change to mitigate the negative outcomes.

The findings indicate that people who are more concerned about the climate change consequences are more likely to learn more about the phenomena, which in turn could lead to a deeper understanding. The results may suggest that efforts aimed to increase the awareness of climate change risks could simultaneously increase public understanding of the issue.

On the other hand, the results indicate that the amount of causal relationships people in Lake Victoria and Lagos included in their MM of climate change is not explained by their level of perceived risk. Since both regions are severely affected by flooding and droughts (Müller et al., 2014), it was expected that people who feel geographically closer to the climate change event are more likely to perceive climate change as a significant threat. This close geographical threat was expected to lead to higher risk perceptions explaining more causal relations (Bostrom, 2017; McDonald et al., 2015).

5.4 Implications

5.4.1 Theoretical implications

The current study provided valuable empirical insights into the relationship *between gender, risk perception*, and MM complexity in the context of climate change causes and consequences. Differences in MM complexity have been discerned by quantitively comparing the MM of climate change perceptions elicited through the M-Tool application, allowing to compare MM complexity between groups.

The research explored how MM differs per region and which variables explain a variation in complexity. The study provided empirical evidence extending the general body of literature concerning MM complexity. It is the first to investigate MM complexity in Lagos, and it extends a single study investigating MM complexity in Lake Victoria (van den Broek et al., 2023). Specifically, van den Broek et al. (2023) examined differences in MM complexity regarding the drivers of Nile perch stock fluctuations among Tanzanian fishermen. Current study extends this research by assessing differences in MM complexity related to climate change, thus a different system. Additionally, the sample in current study aims to generalize to the broader population of the region, in contrast to the sample of van den Broek et al. (2023) which consisted solely of fishermen.

Mental model complexity of climate change comparing consequences with causes

The empirical finding that the MM of climate change consequences includes more concepts than MM of climate change causes may be explained by other studies. Axelrod et al. (1996) suggest that people tend to perceive climate change consequences solely in a negative light, while climate change causes are attributed both positively and negatively environment. Wolf & Moser (2011) suggest that people may believe that they have greater control over the consequences of climate change than the causes and that people are cognitively more engaged with the consequences of climate change impacting their daily life. The study findings indicate that people tend to have a more comprehensive understanding of the potential consequences of climate change but may not fully grasp the underlying mechanisms that are causing it, which can be problematic because addressing the root causes of climate change is crucial to develop effective solutions. Policy makers can enhance awareness about the underlying mechanisms of climate change to ensure that people and organizations are equipped to make informed decisions. For instance, people may understand that climate change can result in more frequent severe weather events. However, they may not comprehensively understand the underlying causes of climate change, such as greenhouse gas emissions from burning industrial fossil fuels. This lack of understanding can lead to a lack of support for measures that can address the root causes of climate change, such as implementing policies to reduce emissions.

Gender and climate change mental model complexity

There is no consistent relationship between *gender* and *risk perception* and *MM complexity* between the two regions. Gender explains the amount of included concepts in a MM of the causes of climate change in Lake Victoria but not in Lagos. Another regional difference is that the level of perceived risk explains the amount of included concepts in a MM of the causes of climate change in Lagos but not in Lake Victoria.

Secondly, the empirical results demonstrate differences between regions in whether the MM of the causes or consequences of climate change are more complex, extending literature explaining variation in MM between geographical regions (Hoffman et al., 2014; Jones et al., 2011; Atran., 2002). Current research results indicate regional differences in climate change MM: supporting and extending prior literature on MM. Previous research has shown that MM may differ by region, as individuals within a culture may develop converging mental models through knowledge-sharing (Jones et al., 2011; Aminpour et al., 2020; Henly-Shepard et al., 2015). The findings also extend a study of van den Broek et al. (2023), proving that the MM complexity of Tanzanian fishermen indeed varied across regions, thereby illustrating the influence of regional contexts on MM complexity.

Furthermore, variation in MM complexity between genders has not yet been explored in Lake Victoria and Lagos. It was found that gender did not consistently explain differences in MM complexity of climate change, except for the amount of included concepts in Lake Victoria for MM of the causes of climate change. This study extends existing literature through emphasizing the lack of gender as consistently explaining differences in MM complexity of climate change, which is consistent with studies by Sanchez et al. (2012) and Boissiere et al. (2013) that concluded that gender was not significantly explaining climate change perceptions and perceived consequences of climate change.

The finding that gender does not explain MM complexity contradicts prior research suggesting that MM of climate change between gender may differs (Pearson et al., 2017; Ballew et al., 2018;., Phelan et al., 2020).

Risk perception and climate change mental model complexity

The findings of current study extends theoretical understanding of the influence of risk perception on MM complexity. The study suggests that people with a higher risk perception of climate change tend to include a higher amount of concepts in their MM of the causes and consequences of climate change. This finding is consistent with literature suggesting that people who perceive a higher risk may feel a need to understand climate change in greater detail, leading to greater attention and awareness of its consequences, resulting in a more complex mental model (Barnes, 2019). However, the study found no relationship between risk perception and the amount of causal relationships included in the MM of the causes and consequences of climate change. This may suggest that people who perceive a higher risk may conduct research to understand certain abstract concepts, such as the release of carbon emissions, but may not conduct integrated research to fully grasp how the relationships between different concepts of climate change are established. For instance, people may understand that carbon emissions cause heat to be trapped in the atmosphere, but may not have a complete understanding of how the increase of carbon emissions from human activities can lead to changes in global temperature and more frequent and severe flooding or droughts.

5.4.2 Practical implications

The results of this study offer contributions to the efforts to address climate change in Lake Victoria and Lagos. This study can provide valuable information to develop targeted communication strategies that can encourage action on climate change.

To improve people's adaptive capacity to mitigate climate change, it may be necessary to develop effective communication strategies that take into account differences in the complexity of MM. First, a practical implication for communication strategies is to target efforts towards increasing people’s MM complexity of climate change for groups with a lower MM complexity. People with a higher MM complexity may consider more relevant concepts and causal relationships between concepts, indicating system-thinking capabilities necessary to mitigate climate change (Curseu, Schruijer & Boros, 2007). For example, a person with a higher MM complexity may understand that industrialization causes the increased release of greenhouse gas emissions into the atmosphere, which subsequently contributes to changing weather patterns. This understanding can influence people to support using renewable energy sources to reduce greenhouse gas emissions emitted from industries.

In contrast, a person with a lower MM complexity may not understand the relationship between industrialization and climate change and therefore, may not support policies to reduce industrial greenhouse gas emissions. Moreover, when people are able to identify several causal relations between concepts, for instance, the understanding that deforestation contributes to climate change and that planting trees can help to reduce greenhouse gas emissions, they will be more likely to support reforestation initiatives compared to a simpler MM where people solely identify the causal relation that greenhouse gas emissions cause climate change. Thus, the findings of this study indicate that there are several differences in the complexity of mental models related to climate change. These differences can be addressed through targeted communication strategies, which aim to improve people's understanding of the concepts and causal relationships involved in climate change. By doing so, people will be better equipped to adapt to a changing environment. The following sections provides an elaboration on the practical implications that arose from the observed content differences in MM, as evidenced by current research.

Regional differences in climate change mental models

The results demonstrated that the perceived climate change causes in Lake Victoria *deforestation, drought, land degradation, and rainfall* oppose the perceived causes in Lagos, where people identify *greenhouse gas emissions, population growth, urban development, and waste burning* as primary causes. Since the perceived cause of climate change explains the person's preferred mitigation policy (Bostrom et al., 2012), the differences in MM content of the causes of climate change between regions can have practical implications on risk communications and pose obstacles for mitigation policy (Sterman, 2008). To illustrate, a practical implication regarding the regional differences in perceived causes of climate change is that mitigation policies can be tailored to the specific causes identified in each region. For instance, in Lagos, measures to mitigate greenhouse gas emissions, reduce waste incineration, and manage population growth will receive more support. In contrast, in Lake Victoria, policies prioritizing deforestation and land degradation may receive more support.

To develop effective mitigation strategies for climate change, policymakers and stakeholders need to comprehend both the actual causes and the public's perceptions of those causes. It is crucial to recognize that the public's perception may not always correspond with scientific reality. Consequently, policies that solely target the perceived causes most supported by the public may not effectively mitigate climate change. To tackle this issue, evaluating the MM of people in Lake Victoria and Lagos for accuracy and identifying any misbeliefs is recommended (de Bruin & Bostrom, 2013). For example, suppose the scientific reality is that greenhouse gas emissions from industry instead of the perceived deforestation are the primary cause of climate change in Lake Victoria. In that case, efforts can be made to educate the public on this topic and its relation to climate change (Morgan et al., 2001).

Climate change requires international cooperation because it is a global problem that affects all regions of the world. The emission of greenhouse gases contributing to climate change is not limited to one region or country (Adedeji O. et al., 2014). Therefore, mitigating climate change requires the collaboration of all countries to achieve a substantial impact. However, current study results demonstrated that climate change's perceived causes and effects vary between Lake Victoria and Lagos. As a result, international efforts to address climate change shall consider each region's unique and opposing perceived causes. To do so, policies and regulations designed to mitigate climate change shall be tailored to address the specific causes of climate change in each region to receive support for these policies.

As the current study results indicate, MM complexity of climate change varies by region, potentially posing challenges to private-sector international cooperation. Divergent priorities and strategies may hinder collaboration, as regions may prioritize different solutions to address climate change. For example, one country may prioritize reducing greenhouse gas emissions from industry, while another may focus more on reforestation strategies. Sustainable innovations mitigating climate change can create new opportunities for regional private collaboration. International organizations are encouraged to share resources in developing sustainable innovations that address climate change. By engaging in private collaboration and sharing resources, regions can capitalize on each other's strengths and expertise to drive innovative solutions that provide mutual benefits. This approach can foster new partnerships, enhance investment opportunities, and facilitate the creation of innovative technologies mitigating climate change that can be leveraged across borders.

Mental model complexity of climate change comparing consequences with causes

The study's findings suggest that MM of climate change consequences consists of a higher amount of concepts than MM of climate change causes. The differences in MM of climate change causes and consequences may indicate that people are considering adapting to climate change's consequences, such as exploring alternative economic activities or migrating to more fertile land. It also suggests that people may feel disempowered or lack the knowledge required to address the root causes of climate change (Wolf & Moser, 2011). A MM consisting of a limited amount of included concepts of climate change causes is problematic since insufficient knowledge of the causes will prevent people from supporting policies to mitigate climate change. For example, an incorrect or overly simplified MM of the causes of climate change can hinder individual engagement with mitigation and adaptation implications. If people believe climate change is caused by factors beyond human control, such as God, they may not support policies to reduce greenhouse gas emissions.

According to a study by the BBC (2009), the limited understanding of climate change causes among African citizens may be due to a lack of understanding that climate change is caused by factors beyond their own experience or region. This can lead them to overlook that international pollution may partly or increasingly affect their local droughts and floods. As suggested by the results of the current study, a MM of only a few included concepts of the causes of climate change indicates a lack of information necessary for people in Lagos and Lake Victoria to understand how to adapt to climate change adequately. They may lack the knowledge to influence international organizations and their national government to demand an appropriate response to mitigate the causes of climate change. When people in Lake Victoria and Lagos do not have a greater understanding of the multiple scientifically accurate causes of climate change, those impacted by climate change may not be able to recognize stakeholders beyond themselves or their region who contribute to climate change. As a result, they may be unable to hold these stakeholders accountable or confront them with their responsibilities to mitigate climate change.

Gender and climate change mental model complexity

Additionally, the research demonstrated that in Lake Victoria, men include more concepts in their MM of climate change causes than women. The results suggest that efforts to improve the amount of concepts in MM of climate change causes in Lake Victoria should consider gender differences. However, the inclusion of more concepts by men in Lake Victoria does not necessarily indicate that men have more knowledge of the causes of climate change than women. One reason may be that people with a higher level of system-thinking capabilities have the ability to simplify complex relationships. Less complex MM may allow women in Lake Victoria to focus on the most important causes of climate change (Levy et al., 2018; Hallbrendt et al., 2014). Thus, it is not guaranteed that the MM will become more complex when increasing female knowledge of the causes of climate change in Lake Victoria.

Suppose women in Lake Victoria include less concepts in their MM due to knowledge limitations. In that case, interventions targeting women may be necessary to increase their understanding of MM of the causes of climate change. Therefore, interventions that are designed to address these gender-specific barriers can lead to an increase in the number of included concepts in women's mental models. Focusing on the least complex MM with the fewest included concepts can be helpful as it can provide a foundation for building more complex MM over time.

According to Özesmi (2004), people with higher MM complexity are better equipped to navigate dynamic environments and complex issues like climate change. This is because including more concepts allows for a broader range of potential solutions to be identified. Thus, it may benefit women in Lagos to acquire a more diverse range of knowledge about the causes of climate change to better adapt to their changing environment. By broadening their understanding of the causes of climate change, women in Lagos will be better equipped to absorb and process new information, enhancing their adaptive capacities (Jones et al., 2011).

The study did not find a significant gender difference in the number of included causal relations in MM of the causes and consequences of climate change. This suggest that the need for gender-specific interventions may not be required for improving conceptual understanding of the connections between the causes and consequences of climate change.

Risk perception and climate change mental model complexity

The third research question investigated whether risk perception levels explain differences in MM complexity. The research findings suggest that a higher perception of climate change risk explains a higher amount of included concepts at MM of the causes and consequences of climate change in Lagos and a higher amount of included concepts at MM of the consequences of climate change in Lake

Victoria. Those findings indicate that communication strategies can focus on increasing people's perception of climate change risk to enlarge the amount of included concepts. Enlarging the amount of included concepts in a person's MM is recommended to gain a broader understanding of climate change concepts. A system thinking approach can benefit people in making better-informed decisions about climate change because they are better aware of the interconnectedness of multiple causes and consequences of climate change (Levy et al., 2018; Calori et al., 1994).

According to Spence et al. (2012), people who perceive climate change as an immediate threat reported higher risk perceptions. Although the mean perceived risk scores on a 5-point Likert scale were not notably low (*Lagos: M=3.9, SD=0.80, Lake Victoria: M=4.33, SD=0.56*) (see Appendix B), people who possess a more complex MM in Lagos and Lake Victoria may have improved systemic thinking abilities, which could aid in their understanding of the various causes and consequences of climate change.

One way to increase the perception of climate change as a threat can be by disseminating more information on its consequences. Additionally, emphasizing the destructive consequences of inactivity can underline the need to adopt mitigation measures with a sense of urgency. It should be emphasized that although it is important for people to understand several causes and consequences of climate change, too much complexity can danger a feeling of disempowerment, giving people a sense that they cannot take action to deal with all causes of climate change. To minimize the risk of feeling disempowered, it is suggested to predominantly educate about climate change causes and consequences within the communities' adaptive capacities (IIED, 2009).

In conclusion, this research provides crucial practical implications for mitigating climate change in Lake Victoria and Lagos. The findings suggest that effective communication strategies should target specific groups to increase their knowledge and system-thinking capabilities of climate change. A higher MM complexity can improve decision-making. Even though people with higher MM complexity may take longer to evaluate the connectedness of various causes and consequences of climate change, they are less likely to miss unforeseen impacts of innovative technology or policy interventions (Levy et al., 2018). Therefore, a rather similar MM complexity between regions and gender is likely to promote effective collaboration for sustainable business innovation and facilitate the identification of new solutions to mitigate the impact of climate change (Blackman & Davidson., 2005). Additionally, this could enhance support for policy implementation and technology adoption incentivizing sustainable practices (Bostrom et al., 2012).

5.4.3 Avenues for future research

Future research is recommended to explore the theoretical implications of the differences in MM complexity between the causes and consequences of climate change. Specifically, it is advised to examine the underlying mechanism which explains those MM complexity differences and the extent to which partly positive (causes) or negative (consequences) perceptions explain these differences. Additionally, it is recommended to determine to what extent the perceived sense of control over climate change consequences is an underlying mechanism that explains differences in MM of climate change causes and consequences.

Also, to ensure the development of effective mitigation strategies for climate change it is recommended to compare the public's perceived climate change causes with scientific reality. Policies that solely target the perceived causes most supported by the public may not effectively mitigate climate change. Subsequently, any misbeliefs or can be bridged through educational communication campaigns to overcome knowledge limitations (Moon et al., 2002).

A third avenue for future research related to observed gender-differences is that it is questionable whether the inclusion of more concepts by men in Lake Victoria indicates that men have more knowledge of the causes of climate change than women, or that women simplify complex relationships due to a higher level of system-thinking capabilities. To recommend appropriate interventions, further research shall identify whether women have a less complex MM of climate change causes due to knowledge limitations. Also, future research could examine whether the lack -except the aforementioned amount of included concepts for the MM of climate change causes in Lake Victoria- of gender explaining further differences in MM complexity observed in Lake Victoria and Lagos is unique to these regions or reflects a broader trend in other regions affected by climate change.

Further research is required to investigate why climate change risk perception solely explains the number of included concepts and not the amount of included causal relations in MM of climate change consequences. One possible explanation for this observation is that people who perceive a greater risk of climate change may not necessarily possess a more detailed understanding of the causal relationships between various concepts related to climate change consequences. It is plausible that people with a higher perception of risk may have a greater awareness or motivation to recognize and identify the different causes and consequences of climate change. However, they may not understand how these concepts are interconnected, which may indicate a lack of integrated research.

Lastly, it would be valuable to understand which regional differences cause risk perception to explain the amount of included concepts for MM of climate change causes in Lagos but not in Lake Victoria. It is plausible that a contributing factor may be differences in access to information between the two regions about the causes of climate change. People in Lagos may have greater access to information when feeling vulnerable to the effects of climate change or may have more time to educate themselves, leading to greater identification of concepts causing climate change. This explanation is recommended to be further investigated.

5.5 Limitations

Pre-determined concepts

This study provided valuable insights into understanding the differences in MM complexity of climate change causes and consequences in Lake Victoria and Lagos; however, several limitations that could have affected the study results should be addressed. Despite that the selection of pre-determined concepts in the M-Tool enhances the replicability and comparability across larger samples (van den Broek et al., 2021), it restricts participants from adding concepts to their MM (van den Broek et al., 2020), which limits the amount of potential included concepts and causal relations. Thus, participants would may generate a more complex MM if they could include more concepts. To illustrate, a participant may perceive additional causes or consequences of climate change that were not pre-determined an thus could not be selected in the mapping procedure. To mitigate the threat that perceived climate change causes or consequence were not included in the mapping procedure, the M-tool procedure involved verifying if the pretest group overlooked any concepts when eliciting their MM.

It is on the other hand possible that the M-Tool may measures MM in a more complex manner than participants' real-world perception because pre-determined concepts prompt causes and consequences that participants may not be able to generate independently.

Level of understanding identified causal relationships

It should also be acknowledged that in the elicited MM, an arrow represents the identification of a causal relation between concepts, and the number of causal relations indicate a higher MM complexity. Since the M-Tool does not capture the meaning of the causal relations, in other words, the underlying mechanism explaining how and why one climate change concept influences the other. It remains unknown whether the drawn arrow indicates that the participant has a detailed, complex understanding of the causal relationship or a generalized understanding of the underlying mechanisms. A mixed-method approach is recommended to understand the level of detailed thinking more comprehensively. During a mixed-method approach, the quantified results of M-Tool will then be supplemented with interviews to generate a more detailed understanding of someone’s climate change MM.

Technological illiteracy

Another limitation of the research instrument is the elicitation through a technological device since the MM is drawn on a tablet. Not all participants in the current study were familiar with this technology: several participants reflected that it was their first time using a tablet. To ensure that M-Tool is also accessible for participants with low levels of computer literacy, the research assistants assisted participants in operating the tablet. Researchers shall be aware that the data collection process would be more time intensive and require more participant engagement for populations with less technological literacy.

Inter-observer consistency

Following data collecting limitations, the presence of research assistants during the data collection tasks threatens the internal reliability of the process. There can be a lack of consistency between research assistants in their supervision, harming inter-observer consistency (Bryman, 2020). LaMere et al. (2020) demonstrated that complex MM are time-consuming to elicit, so it seems plausible to believe that when the research assistant does not encourage the participant to complete the full 60 minutes available to draw the MM, this frequently leads to less complex MM.

Also, there can be a lack of consistency in whether and how intensively the research assistant prompted to include several causal relations between concepts. Providing guidance and training to research assistants to emphasize the importance of prompting causal relationships may help address the issue of inconsistent prompting. Additionally, monitoring research assistants' performance by comparing the average complexity of the elicited MM under their supervision can help identify any potential problems with inconsistent prompting during the data collection process. Offering additional training to research assistants whose participants scoring consistency falls below the average MM complexity can subsequently improve the internal reliability of the data collection process.

Monetary compensation participants

The participant selection could be a final threat to the internal validity of the study. This threat occurs because some participants may only participate for financial compensation and may not take the elicitation task seriously (Bryman, 2020). When participants do not take their elicitation task seriously, their elicited MM may not accurately reflect their true understanding or beliefs of the causes and consequences of climate change, leading to biased results. One potential solution to address this limitation is introducing a screening process to verify that participants are fully engaged in the study beyond monetary compensation. Additionally, it shall be considered providing a smaller financial incentive to participants in order to discourage them to from participating solely for monetary gain. Poor participant selection can result in unreliable results, conclusions, and recommendations, resulting in negative scientific consequences for future research in the field. Future studies could consider implementing more stringent screening measures, such as those earlier outlined, to ensure participants are incentivized to provide accurate and reliable responses to the MM elicitation task.

Low R-squared value

Another limitation of this research is the low R-squared value for the multiple linear regression model. However, it is important to note that the aim of this research is not to accurately explain the MM complexity of the causes and consequences of climate change based on the independent and control variables included in the model. Instead, the aim is to explain differences in MM complexity based on *risk perception and gender.*. Therefore, a low R-squared value is not necessarily a significant concern for current research. However, the low R-squared value indicates that the independent variables explain a low variation in MM complexity. It is recommended that future research identifies additional variables which explain the variation in MM complexity. Doing so makes it possible to obtain a more comprehensive understanding, which can contribute to a more accurate explanation of MM complexity.

A suggestion for other variables explaining variation in MM complexity of climate change can be differences in cultural beliefs. Some cultures may perceive climate change as a natural occurrence beyond human control. Subsequently, people in those cultures may have less complex MM of climate change causes and consequences because they do not perceive themselves as having a role in mitigating or adapting to climate change. Their MM may not account for human activities that cause climate change. Religious beliefs could also be a valuable area for further investigation into the variables that influence MM complexity of climate change causes and consequences. For instance, believing in god may lead to a perception that human actions cannot mitigate climate change, resulting in less complex MM. The theory that religious people have a less complex MM coheres with a study by BBC concluding that most Ethiopians felt that God alone has the power to change the weather, while the Ethiopians had little knowledge of climate change and global warming (BBC, 2009). Conversely, in indigenous traditions that emphasize environmental stewardship, people may believe that they have a responsibility to care for the environment. This sense of responsibility, combined with a deep connection to the natural world, may lead to more understanding of the causal relationships impacting their environment, thus resulting in more complex MM. A study of Indigenous Australians acknowledged that indigenous people have a comprehensive understanding of climate change, where flora-fauna-climate interactions indicate indigenous people of changes in seasonal weather patterns (Green & Raygorodetsky, 2010).

Causality

Another limitation is that solely causal relationships between variables are identified, not the underlying causes or mechanisms. In order to fully understand the relationships, a deeper understanding of the underlying mechanisms is necessary. This understanding will allow to gain valuable insight into questions such as why there are gender differences in MM of climate change and why risk perception explains the amount of included concepts at someone's MM of climate change consequences but does not explain the amount of included causal relations at someone's MM of the causes and consequences of climate change?

Furthermore, due to the non-experimental research design, statistical results only determine a relationship between dependent and independent variables and as aforementioned do not establish causality (Bryman, 2012). It is highly unethical to use experimental research design to study climate change MM. Manipulating variables may expose participants to misinformation about climate change and manipulate their perceived risk level, which could negatively affect their attitudes toward the environment. For example, intentionally providing misinformation to participants about the severity of climate change issues could result in behaviours such as ignoring environmental issues and continuing to engage in environmentally harmful practices with impactful real-world consequences.

Elicitation at a single point in time

The MM in the current study were elicited at a single point in time, leaving room for the possibility that uncontrolled external events may have influenced their elicitation. For instance, extreme weather or temporarily increased media attention on weathering events could have impacted the MM. Abrupt climate change events could have led to heightened awareness and identification of additional relations related to the concept of climate change. Given climate change's dynamic and rapidly changing nature, future research would benefit from a non-experimental design, such as longitudinal studies. A longitudinal study would allow for assessing changes in MM complexity over time, as MM are prone to change and evolve (Moon et al., 2019). One possible opportunity for further research could be to investigate how the MM complexity of climate change causes and consequences develop over time. Understanding how MM of climate change develop over time can benefit policymakers and organization in determining effective strategies to mitigate climate change. For example, suppose research shows that the MM complexity increases over time. In that case, it may indicate that people are becoming aware of more climate change causes and consequences, potentially resulting in more common ground for collaboration on innovation development. There is a higher chance of a shared understanding of climate change and thus, collaboration for sustainable business innovation when a MM is more complex MM (Bostrom et al., 2012; Blackman & Davidson, 2005). On the other hand, if the MM complexity is decreasing over time, it may suggest that awareness communication campaigns are not achieving their intended impact. This could indicate a need for alternative communication strategies to more effectively convey complex information to increase accurate climate change understanding.

Generalizability

The results from current research provided valuable insights into understanding the contribution of *risk perception* and *gender* to MM complexity. However, it is important to note that the study's geographical scope was limited to Lake Victoria and Lagos, and the MM complexity of climate change causes and consequences may vary greatly across different socioeconomic and cultural contexts. Hence, future research should investigate the extent to which the findings can be generalized beyond the studied region. Nevertheless, the study provides an important empirical foundation for developing and testing hypotheses concerning the MM complexity of climate change.

6. Conclusion

The purpose of this research was to gain insight into the MM complexity of climate change causes and consequences. Two African regions, Lake Victoria and Lagos, which are severely impacted by climate change, were selected to assess the complexity of MM. Differences in MM complexity have been discerned by quantitively comparing the MM of climate change perceptions elicited through the M-Tool application, allowing to compare MM complexity between groups.

The first research question investigated whether MM of climate change consequences consists of more concepts than MM of climate change causes. It was found that people tend to have a more comprehensive understanding of the potential consequences of climate change compared to the causes. When people in Lake Victoria and Lagos lack understanding of the multiple scientifically accurate causes of climate change, those impacted by climate change may not be able to recognize stakeholders beyond themselves or their region who contribute to climate change. As a result, they may be unable to hold these stakeholders accountable or confront them with their responsibilities to mitigate climate change.

The second question addressed whether gender explains differences in MM complexity. No consistent gender differences in MM complexity of climate change causes and consequences were found, except for the amount of included concepts of MM of climate change causes in Lake Victoria. The results suggest that efforts to improve the amount of concepts in MM of climate change causes in Lake Victoria should take into account gender differences. However, the inclusion of more concepts by men in Lake Victoria does not necessarily indicate that men have more knowledge of the causes of climate change than women. This is because people with a higher level of system-thinking capabilities may have the ability to simplify complex relationships. Thus, it is not guaranteed that the MM will become more complex when increasing female knowledge of the causes of climate change in Lake Victoria. To recommend appropriate interventions, further research shall identify whether women in Lake Victoria have a less complex MM of climate change causes due to knowledge limitations or whether system-thinking capabilities led them to focus on the most important concepts causing climate change.

The third question investigated whether risk perception levels explain differences in MM complexity. The results indicated a positive relationship between a greater perceived risk in Lagos, resulting in a higher amount of included concepts at the MM of the causes and consequences of climate change, and in Lake Victoria, a higher amount of included concepts at MM of the consequences of climate change. Those findings indicate that communication strategies can focus on increasing people's perception of climate change risk to enlarge the amount of included concepts. Enlarging the amount of included concepts in a person’s MM is recommended to gain a broader understanding of climate change concepts. A system thinking approach can benefit people in making better-informed decisions about climate change because they are better aware of the interconnectedness of multiple causes and consequences of climate change. It should be emphasized that although it is important for people to understand several causes and consequences of climate change, too much complexity can danger a feeling of disempowerment, giving people a sense that they cannot take action to deal with all causes of climate change.On the other hand, the results indicate that the amount of causal relationships people in Lake Victoria and Lagos included in their MM of climate change is not explained by their level of perceived risk. The results may indicate that people with a higher perception of risk may have a greater level of awareness to identify different climate change concepts. However, they may not understand how these concepts are interconnected, which may indicate a lack of integrated research.

This study makes a valuable contribution to the literature on comparing MM complexity differences across *gender* and *risk perception levels*, as well as extending the literature on MM complexity of climate change causes and consequences. However, it is important to note that the study only identifies relationships between variables, not underlying causes or mechanisms. Additional research is recommended to gain a deeper understanding of the identified relationships and the underlying mechanisms causing it.

7. References

Abel, N., H. Ross, and P. Walker. 1998. Mental models in rangeland research , communication and management. *Rangeland Journal* 20L77-91.

Adedeji, O. et al. (2014). Global Climate Change. Journal of Geoscience and Environment Protection, 2, 114-122. http://dx.doi.org/10.4236/gep.2014.22016

Akinwande, M. O., Dikko, H. G., & Agboola, S. (2015). Variance inflation factor: as a condition for the inclusion of suppressor variable(s) in regression analysis. Open Journal of Statistics, 05(07), 754–767. https://doi.org/10.4236/ojs.2015.57075

Aluko, O. E. (2011). The Impact of Urbanization on Housing Development: The Lagos Experience, Nigeria. Ethiopian Journal of Environmental Studies and Management, 3(3). https://doi.org/10.4314/ejesm.v3i3.63967

Arnell, N., Livermore, M., Kovats, S., Levy, P., Nicholls, R. J., Parry, M. A. J., & Gaffin, S. (2004). Climate and socio-economic scenarios for global-scale climate change impacts assessments: characterising the SRES storylines. *Global Environmental Change-human and Policy Dimensions*, *14*(1), 3–20. https://doi.org/10.1016/j.gloenvcha.2003.10.004

Atran, S., Medin, D., Ross, N., Lynch, E., Vapnarsky, V., Ek', E. U., Coley, J., Timura, C., & Baran, M. (2002). Folkecology, cultural epidemiology, and the spirit of the commons. Current Anthropology, 43(3), 421–450. https://doi.org/10.1086/339528

Aminpour, P., Gray, S. A., Jetter, A. J., Introne, J. E., Singer, A., & Arlinghaus, R. (2020). Wisdom of stakeholder crowds in complex social–ecological systems. Nature Sustainability, 3(3), 665 191–199. https://doi.org/10.1038/s41893-019-0467-z

Axelrod R. (Ed.). (1976). Structure of decision: The cognitive maps of political elites. Princeton, NJ: Princeton University Press.

Ballew, M., Marlon, J., Leiserowitz, A., & Maibach, E. (2018). Gender Differences in Public Understanding of Climate Change. Yale Program on Climate Change Communication. https://climatecommunication.yale.edu/publications/gender-differences-in-public-understanding-of-climate-change/

Barnes, S. J. (2019). Out of sight, out of mind: Plastic waste exports, psychological distance and consumer plastic purchasing. *Global Environmental Change-human and Policy Dimensions*, *58*, 101943. https://doi.org/10.1016/j.gloenvcha.2019.101943

Bäthge, S. (2010). Climate change and gender: economic empowerment of women through climate mitigation and adaptation? https://www.oecd.org/dac/gender-development/46975138.pdf

BBC. (2009). Least responsible, most affected, least informed: public understanding of climate change in Africa.

Blackman, D. & Davison, G. (2005). The role of mental models in innovative teams. *European Journal of Innovation Management*, *8*(4), 409–423. https://doi.org/10.1108/14601060510627795

Boko, M., I. Niang, A. Nyong, C. Vogel, A. Githeko, M. Medany, B. Osman-Elasha, R. Tabo and P. Yanda, 2007: Africa. Climate Change 2007: *Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge University Press, Cambridge UK, 433-467

Bostrom, A., O'Connor, R. E., Böhm, G., Hanss, D., Bodi, O., Ekström, F., Halder, P., Jeschke, S., Mack, B., Qu, M., Rosentrater, L., Sandve, A., & Sælensminde, I. (2012). Causal thinking and support for climate change policies: International survey findings. *Global Environmental Change*, *22*(1), 210–222. https://doi.org/10.1016/j.gloenvcha.2011.09.012

Bostrom, A. (2017). Mental models and risk perceptions related to climate change. Oxf. Res. Encycl. Clim. Sci., 1–31. doi: 10.1093/acrefore/9780190228620.013.303

Boissière, M., Locatelli, B., Sheil, D., Padmanaba, M., & Sadjudin, E. (2013). Local perceptions of climate variability and change in tropical forests of Papua, Indonesia. Ecology and Society, 18(4). https://doi.org/10.5751/es-05822-180413

Boxtel, W. V., & Van den Broek, K. L. (2021). Data publication platform of Utrecht University. Opgehaald van M-Tool data analysis script: https://public.yoda.uu.nl/geo/UU01/Y8GP93.htm

Breusch, T., & Pagan, A. (1979). A simple test for heteroscedasticity and random coefficient variation. Econometrica, 47(5), 1287. https://doi.org/10.2307/1911963

Bryman, A., 2012. *Social Research Methods*. 4th ed. New York: Oxford University Press.

Brügger, A., Dessai, S., Devine-Wright, P., Morton, T. H., & Pidgeon, N. F. (2015). Psychological responses to the proximity of climate change. *Nature Climate Change*, *5*(12), 1031–1037. https://doi.org/10.1038/nclimate2760

Carey, S. (1986) 'Cognitive science and science education'. American Psychologist, 41(10), 1123-1130. Chaiken, S. and Trope, Y. (1999) Dual-process theories in social psychology. New York: Guilford Press

Chong Ngo, C. (2021). Climate change risk communication : How message frames shape perceptions of risks and efficacy, and influence behavioural intentions to climate change adaptation and mitigation. https://doi.org/10.18174/554534

Chu, H., & Yang, J. Z. (2020). Risk or efficacy? How psychological distance influences climate change engagement. Risk Analysis, 40(4), 758–770. https://doi.org/10.1111/risa.13446

Conway D (2011) Adapting climate research for development in Africa. Wiley Interdisciplinary Reviews: Climate Change, 2, 428–450.

Curseu, P. L., Schruijer, S. G. L., & Boros, S. (2007). The effects of groups' variety and disparity on groups' cognitive complexity. Group Dynamics: Theory, Research and Practice, 11(3), 187-206.

Das, K. R. (2016). A brief review of tests for normality. American Journal of Theoretical and Applied Statistics, 5(1), 5. https://doi.org/10.11648/j.ajtas.20160501.12

De Bruin, W. B., & Bostrom, A. (2013). Assessing what to address in science communication. Proceedings of the National Academy of Sciences of the United States of America, 110(supplement_3), 14062–14068. https://doi.org/10.1073/pnas.1212729110

Diffenbach, J. (1982). Influence diagrams for complex strategic issues. Strategic Management Journal, 3, 133–146.

Driver, M., & Streufert, S. (1969). Integrative Complexity : An Approach to Individuals and Groups as Information-Processing Systems. Administrative Science Quarterly, 14(2), 272–283.

Feng, C., Wang, H., Lu, N., Tian, C., He, H., Lu, Y., & Tu, X. (2014). Log-transformation and its implications for data analysis. PubMed. https://doi.org/10.3969/j.issn.1002-0829.2014.02.009

Geheb, K., & Binns, T. (1997). Fishing farmers or 'farming fishermen'? The quest for household income and nutritional security on the Kenyan shores of Lake Victoria. African Affairs, 96(382), 73–93. https://doi.org/10.1093/oxfordjournals.afraf.a007822

Ghasemi, A., & Zahediasl, S. (2012). Normality Tests for Statistical Analysis: A Guide for Non-Statisticians. international journal of endocrinology and metabolism, 10(2), 486–489. https://doi.org/10.5812/ijem.3505

Gray, S. (2018). Measuring systems thinking. Nature sustainability, 1(8), 388–389. https://doi.org/10.1038/s41893-018-0121-1

Gray, S., Hilsberg, J., McFall, A., & Arlinghaus, R. (2015). The structure and function of angler mental models about fish population ecology: The influence of specialization and target species. Journal of Outdoor Recreation and Tourism, 12, 1–13.

Green, D., & Raygorodetsky, G. (2010). Indigenous knowledge of a changing climate. Climatic Change, 100(2), 239–242. https://doi.org/10.1007/s10584-010-9804-y

Haden, V. R., Niles, M. T., Lubell, M., Perlman, J., & Jackson, L. E. (2012). Global and local concerns: What attitudes and beliefs motivate farmers to mitigate and adapt to climate change? PLOS ONE, 7(12), e52882. https://doi.org/10.1371/journal.pone.0052882

Halbrendt, J. et al. Diferences in farmer and expert beliefs and the perceived impacts of conservation agriculture. Glob. Environ. Change 28, 50–62 (2014)

Helgeson, J., Chabay, I., & der Linden, S. van. (n.d.). Learning for sustainability in times of accelerating change. In *The role of knowledge, learning and mens in public perceptions of climate change related risks*. https://doi.org/10.3920/978-90-8686-757-8_21

Henly-Shepard, S., Gray, S. A., & Cox, L. J. (2015). The use of participatory modeling to promote 750 social learning and facilitate community disaster planning. Environmental Science and 751 Policy, 45, 109–122. https://doi.org/10.1016/j.envsci.2014.10.004

Hillson, D. and Murray-Webster, R. (2005) Understanding and Managing Risk Attitude. VT, USA: Gower Publishing.

Hockerts, K. (2015). A cognitive perspective on the business case for corporate sustainability. Business Strategy and the Environment, 24(2), 102–122.

Hoffman, M., Lubell, M., & Hillis, V. (2014). Linking knowledge and action through mental models of sustainable agriculture. Proceedings of the National Academy of Sciences of the United States of America, 111(36), 13016–13021.

Hope KR (2009) Climate change and poverty in Africa. International Journal of Sustainable Development and World Ecology, 16, 451–461.

Howell, D. C. (1982). Statistical Methods for Psychology.

Hsu, H. H., & Lachenbruch, P. A. (2014). Paired T test. Wiley StatsRef: Statistics Reference Online. https://doi.org/10.1002/9781118445112.stat05929

Hulme, M. (2009) Why we disagree about climate change: Understanding controversy, inaction and opportunity. Cambridge: Cambridge University Press

IPCC (2007) Climate Change 2007: The Physical Science Basis. Fourth assessment report of the intergovernmental panel on climate change. Cambridge: Cambridge University Press.

Jones, E., & Pérez, C., Kristjanson, P. M., Cramer, L., Thornton, P. K., Förch, W., & Barahona, C. (2015). How resilient are farming households and communities to a changing climate in Africa? A gender-based perspective. *Global Environmental Change-human and Policy Dimensions*, *34*, 95–107. https://doi.org/10.1016/j.gloenvcha.2015.06.003

Jetter, A. J., & Kok, K. (2014). Fuzzy Cognitive Maps for futures studies-A methodological assessment of concepts and methods. Futures, 61, 45–57.

Jones, N.A., Ross, H., Lynam, T., Perez, P., Leitch, A., (2011). Mental models: an interdisciplinary synthesis of theory and methods. Ecol. Soc. 16.

Jones, N. A., Ross, H., Lynam, T., & Perez, P. (2014). Eliciting mental models: A comparison of interview procedures in the context of natural resource management. Ecology and Society, 19(1), 13. https://doi.org/10.5751/ES-06248-190113

Jurečková, J., & Picek, J. (2007). Shapiro–Wilk-type Test of normality under nuisance Regression and scale. Computational Statistics & Data Analysis, 51(10), 5184–5191. https://doi.org/10.1016/j.csda.2006.08.026

Kaggwa R, Hogan R, Hall B, eds. Enhancing the contribution of weather, climate and climate change to growth, employment and prosperity. Kampala, Uganda: UNDP/NEMA/UNEP Poverty Environment Initiative, 2009.

Kearney, A.R., and Kaplan, S. (1997) 'Toward a methodology for the measurement of knowledge structures of ordinary people: the conceptual content cognitive map'. Environment and Behaviour, 29(5): 579

LaMere, K., Mäntyniemi, S., Vanhatalo, J., & Haapasaari, P. E. (2020). Making the most of mental models: Advancing the methodology for mental model elicitation and documentation with expert stakeholders. Environmental Modelling and Software, 124, 104589. https://doi.org/10.1016/j.envsoft.2019.104589

Leiserowitz, A., Maibach, E., Roser-Renouf, C., & Smith, N. (2010) Climate change in the American Mind: Americans' global warming beliefs and attitudes in June 2010. Yale University and George Mason University. New Haven, CT: Yale Project on Climate Change Communication. http://environment.yale.edu/climate/files/ClimateBeliefsJune2010.pdf

Lemos MC, Kirchhoff CJ, Ramprasad V (2012) Narrowing the climate information usability gap. Nature Climate Change, 2, 789–794

Levy, M. A., Lubell, M. N., & McRoberts, N. (2018). The structure of mental models of sustainable agriculture. Nature Sustainability, 1(8), 413–420. https://doi.org/10.1038/s41893-018-0116-y

Liberman, N., Sagristano M., Trope Y. (2002). The effect of temporal distance on level of mental construal. *Journal of Experimental Social Psychology*, 38, 523–534.

Lorenzoni, I., & Pidgeon, N. F. (2006). Public views on climate change: European and USA perspectives. Climatic Change, 77(1–2), 73–95. https://doi.org/10.1007/s10584-006-9072-z

Maiella, R., La Malva, P., Marchetti, D., Pomarico, E., Di Crosta, A., Palumbo, R., Cetara, L., Di Domenico, A., & Verrocchio, M. C. (2020). The Psychological Distance and Climate Change: A Systematic Review on the Mitigation and Adaptation Behaviors. *Frontiers in Psychology*, *11*. https://doi.org/10.3389/fpsyg.2020.568899

McDonald, R., Chai, H. Y., & Newell, B. R. (2015). Personal experience and the 'psychological distance' of climate change: An integrative review. *Journal of Environmental Psychology*, *44*, 109–118. https://doi.org/10.1016/j.jenvp.2015.10.003

MECCA | Utrecht University. (n.d.). MECCA. https://mecca.sites.uu.nl/

Meijnders, A.L. (1998) Climate change and changing attitudes: effect of negative emotion on information processing. Doctoral dissertation, , Eindhoven: Eindhoven University of Technology.

Molla, A., Di, L., Guo, L., Zhang, C., & Chen, F. (2022). Spatio-Temporal Responses of Precipitation to Urbanization with Google Earth Engine: A Case Study for Lagos, Nigeria. Urban Science, 6(2), 40. https://doi.org/10.3390/urbansci6020040

Moon, K., Guerrero, A.M., Adams, V.A., Biggs, D., Blackman, D.A., Craven, L., Dickinson, H. & Ross, H. (2019). Mental models for conservation research and practice**.** *Conservation Letters*, *12*(3). https://doi.org/10.1111/conl.12642

Moon, K., Guerrero, A. M., Adams, V. M., Biggs, D., Blackman, D. A., Craven, L., Dickinson, H., & Morgan, M., Fischhoff, B., Bostrom, A. and Atman, C.J. (2002) Risk communication: A mental models approach. Cambridge: Cambridge University Press

Morgan, M. G., Fischhoff, B., Bostrom, A., & Atman, C. J. (2001). Risk communication. https://doi.org/10.1017/cbo9780511814679

Muller C, Robertson R (2014) .Projecting future crop productivity for global economic modeling. Agricultural Economics, 45, 37–50.

Newman, M. E. J. (2010). Networks: An introduction. Oxford University Press. 835 https://doi.org/10.1093/acprof:oso/9780199206650.001.0001

Nadkarni, S., & Narayanan, V. K. (2005). Validity of the Structural Properties of Text-Based Causal Maps: An Empirical Assessment. Organizational Research Methods, 8(1), 9–40. https://doi.org/10.1177/1094428104271999

Nor Aishah Ahad, and Teh Sin Yin, and Abdul Rahman Othman, and Che Rohani Yaacob, (2011) Sensitivity of normality tests to non-normal data. Sains Malaysiana, 40 (6). pp. 637-641. ISSN 0126-6039

Osbourne, J. W., & Waters, E. (2002). Four assumptions of multiple regression that researchers should always test. Practical Assessment, Research and Evaluation, 8(2), 2. https://doi.org/10.7275/r222-hv23

Özesmi, U., & Özesmi, S. L. (2004). Ecological models based on people's knowledge: A multi-step fuzzy cognitive mapping approach. Ecological Modelling, 176, 43–64.

Pearson, A. R., Ballew, M. T., Naiman, S., & Schuldt, J. P. (2017). Race, Class, Gender and Climate Change Communication. Oxford Research Encyclopedia of Climate Science. https://doi.org/10.1093/acrefore/9780190228620.013.412

Phelan, A., Ross, H., Setianto, N. A., Fielding, K., and Pradipta, L. (2020). Ocean plastic crisis-mental models of plastic pollution from remote Indonesian coastal communities. *PloS One* 15:e0236149. doi: 10.1371/journal.pone.0236149

Piontek, F., Müller, C., Pugh, T. A. M., Clark, D. S., Deryng, D., Elliott, J., De Jesus Colón González, F., Flörke, M., Folberth, C., Franssen, W., Frieler, K., Friend, A. D., Seneviratne, S. I., Hemming, D., Khabarov, N., Kim, H., Lomas, M. R., Masaki, Y., Mengel, M., Schellnhuber, H. J. (2014). Multisectoral climate impact hotspots in a warming world. *Proceedings of the National Academy of Sciences of the United States of America*, *111*(9), 3233–3238. https://doi.org/10.1073/pnas.1222471110

Pollino, C. A., Woodberry, O., Nicholson, A., Korb, K., & Hart, B. T. (2007). Parameterisation and evaluation of a Bayesian network for use in an ecological risk assessment. Environmental modelling & Software, 22, 1140–1152.

Reyes, R. S., Nguyen, V. M., Schott, S., Berseth, V., Hutchen, J., Taylor, J. E. T., & Klenk, N. (2021). A research agenda for affective dimensions in climate change risk perception and risk communication. Frontiers in climate, 3. https://doi.org/10.3389/fclim.2021.751310

Richert, C., Boschetti, F., Walker, I. S., Price, J. C., & Grigg, N. J. (2017). Testing the consistency between goals and policies for sustainable development: mental models of how the world works today are inconsistent with mental models of how the world will work in the future. *Sustainability Science*, *12*(1), 45–64. https://doi.org/10.1007/s11625-016-0384-2

Sanchez, A. C., Fandohan, B., Assogbadjo, A. E., & Sinsin, B. (2012). A countrywide multi-ethnic assessment of local communities' perception of climate change in Benin (West Africa). Climate and Development, 4(2), 114–128. https://doi.org/10.1080/17565529.2012.728126

Schmidt, A. F., & Finan, C. (2018). Linear regression and the normality assumption. Journal of Clinical Epidemiology, 98, 146–151. https://doi.org/10.1016/j.jclinepi.2017.12.006

Siegel, A. F. (2016). Multiple regression. In Elsevier eBooks (pp. 355–418). https://doi.org/10.1016/b978-0-12-804250-2.00012-2

Simcic Brønn, P., & Brønn, C. (2003). A reflective stakeholder approach: Co-orientation as a basis for communication and learning. Journal of Communication Management, 7(4), 291– 303.

Spence, A., Poortinga, W., & Pidgeon, N. F. (2012). The Psychological Distance of Climate Change. Risk Analysis, 32(6), 957–972. https://doi.org/10.1111/j.1539-6924.2011.01695.x

Statista. (2021). *Adult literacy rate in Sub-Saharan Africa 2001-2020*. https://www.statista.com/statistics/1233085/adult-literacy-rate-in-sub-saharan-africa/

Sterman, J. D. (2008). Risk communication on climate: mental models and mass balance. Science, 322(5901), 532–533. https://doi.org/10.1126/science.1162574

Stern, P. C., Dietz, T., & Guagnano, G. A. (1995). The new ecological paradigm in social-psychological context. Environment and Behavior, 27, 723–743. doi:10.1177/0013916595276001

Streiner, D. L. (2003). Starting at the beginning: an introduction to coefficient alpha and internal consistency. Journal of Personality Assessment, 80(1), 99–103. https://doi.org/10.1207/s15327752jpa8001_18

Taylor, R et al. (2007). Climate change and the aquatic ecosystems of the Rwenzori Mountains, Uganda. (ECRC Research Report 113). UCL Environmental Change Research Centre: London

Tegarden, D. P., & Sheetz, S. D. (2003). Group cognitive mapping: a methodology and system for capturing and evaluating managerial and organizational cognition. Omega, 31(2), 113–125. https://doi.org/10.1016/s0305-0483(03)00018-5

Tjosvold, D. (2008). The conflict-positive organization: It depends upon us. Journal of Organizational Behavior, 29(1), 19–28.

Trope, Y., & Liberman, N. (2010). Construal-level theory of psychological distance. *Psychological Review*, *117*(2), 440–463. https://doi-org.proxy.library.uu.nl/10.1037/a0018963

Uitdewilligen, S., Waller, M. J., Roe, R. A., & Bollen, P. (2021). The Effects of Team mental model Complexity on Team Information Search and Performance Trajectories. Group and Organization Management, 1–35

United Nations. (2019). *Differentiated impacts of climate change on women and men.* Framework Convention on Climate Change (FCCC), Bonn, Duitsland. https://unfccc.int/sites/default/files/resource/sbi2019_inf8.pdf

van den Broek, K., Bolderdijk, J. W., & Steg, L. (2017). Individual differences in values determine the relative persuasiveness of biospheric, economic and combined appeals. Journal of Environmental Psychology, 53, 145–156. https://doi.org/10.1016/j.jenvp.2017.07.009

van den Broek, K. L., Klein, S. A., Luomba, J., & Fischer, H. (2021). Introducing M-Tool: A standardised and inclusive mental model mapping tool. System Dynamics Review, 37(4), 346–355.

https://doi.org/10.1002/sdr.1698

van den Broek, K. L., Luomba, J., van den Broek, J., & Fischer, H. (2023). Content and complexity of stakeholders' mental models of socio-ecological systems. *Journal of Environmental Psychology*, *85*, 101906. https://doi.org/10.1016/j.jenvp.2022.101906

Vincent, K. (2004). *Creating an index of social vulnerability for Africa*. Working Paper 56, Tyndall Centre for CC Research, University of East Anglia, Norwich, UK

Wiedermann, W., & Eye, A.V. (2013). Robustness and Power of the Parametric T Test and the Nonparametric Wilcoxon Test under Non-Independence of Observations. Psychological test and assessment modeling, 55, 39.

Wood, M. D., Bostrom, A., Bridges, T., & Linkov, I. (2012). Cognitive mapping tools: Review 907 and risk management needs. Risk Analysis, 32(8), 1333–1348. 908 https://doi.org/10.1111/j.1539-6924.2011.01767.x

Wood, M. D., Thorne, S., Kovacs, D., Butte, G., & Linkov, I. (2017). mental modeling Approach. Springer New York. https://doi.org/10.1007/978-1-4939-6616-5

Wolf, J., & Moser, S. C. (2011). Individual understandings, perceptions, and engagement with climate change: insights from in-depth studies across the world. Wiley Interdisciplinary Reviews: Climate Change, 2(4), 547–569. https://doi.org/10.1002/wcc.120

World Bank (2011) Africa Development Indicators. World Bank, Washington, DC, USA.

Xiang, C. (2011) 'Why do people misunderstand climate change? Heuristics, mental models and ontological assumptions'. Climatic Change, 108: 1-16.

8. Appendix

Appendix A: Questionnaire

The questionnaire below measuring climate change perceptions is developed to gather data for the MECCA project. As stated in the methodology, Karlijn van den Broek, co-lead of the MECCA project, provided access to the collected data in Qualtrics for analytical purposes. Important to note that the questionnaire in this appendix is shortened: solely questions that are analysed for the current thesis study are presented.

Item	English questionnaire	
	Informed consent	
Intro1	**Introduction** You are invited to take part in this study of climate change perceptions at Lake Victoria. This study was developed by researchers from the University of Bergen (Norway) and Utrecht University (Netherlands), in collaboration with colleagues from Potsdam Institute for Climate Impact Research (Germany), and the University of Nottingham (United Kingdom). The purpose of the interview is to get an understanding of how people at Lake Victoria view climate change and other related issues.	
Intro2	**Participation** Your participation in this interview is completely voluntary. You can quit at any time without providing any reason and without any penalty. Your contribution to the study is very valuable to us and we greatly appreciate your time taken to complete this interview. We estimate that it will take between 40-60 minutes to complete the interview. We will first ask you to conduct a task on the tablet in which you will draw a picture of your understanding of climate change. After this task we have a few more questions for you. Some of the questions require little time to complete, while other questions might need more careful consideration. Please feel free to skip questions you do not feel comfortable answering. You can also ask the interviewer to clarify or explain questions you find unclear before providing an answer. Your answers will be noted by the interviewer. The data you provide will be used for scientific purposes, including presentations at academic conferences or publications in scientific journals. Only general patterns in the data will be reported through these outlets. Your individual responses will not be presented or published.	
Intro3	**Data Protection** Everything you say in this interview will be confidential and completely anonymous. This means that we will not ask for your name, date of birth, or any other personal information that can be traced to you by us or a third party. Your answers will be shared between the research team in Norway, Germany, the Netherlands, and the United Kingdom. The data will be securely stored in encrypted databases in accordance with the European Union General Data Protection Regulation and Personal Data Act. Only completely anonymized data may later be shared with other researchers. At the end of the interview, you will be provided with a link to our website where you can find additional information about the project as well as contact information to request reports and publications from the project if needed.	
Consent	Do you have any questions about the study? [RA: please take your time to answer any questions related to the survey by the participants before you proceed]. If you are satisfied with the information that you have received about this study and you are willing to participate, I will tick the 'yes' option with your permission before starting the interview. If you do not want to participate, we will end the interview now.	
	Yes	No

Part 1	The following survey consists of three parts. The first part refers to the task that you have just completed, where you drew a model using various images. In the first part of the survey, we will show you these images again and ask you a few more questions about the things the images represent.
	In this second part of the survey, we would like to ask you a few more questions about your views on climate change.
RiskPerception	6. How serious a threat is climate change to the following: [RA: please show the participant the showcard 4]
Show card 4	No serious threat at all | Somewhat serious threat | Moderate threat | Serious threat | Very serious threat
RiskPerception1	You personally?
RiskPerception2	The people here?
RiskPerception3	Humanity as a whole?
RiskPerception4	The natural environment?
RiskPerception5	7. How likely do you think it is that you will personally be harmed by climate change in your lifetime? [RA: please show the participant the showcard 5]
Showcard 5	Very unlikely | Unlikely | Neither unlikely nor likely | Likely | Very likely
RiskPerception6	8. How likely do you think it is that people here will be harmed by climate change within your lifetime? [RA: please show the participant the showcard 4]
	In the final part of the survey, we just have a few final questions about you.
Gender	16. What is your gender? [Note to interviewer: Do not read out options, ask and record. For clarity purpose, you should ask the participant to confirm the option you observed and record on the tablet]
	Man | Woman | Non-binary | Prefer not to say
Age	17. What is your age (in years)?
Nationality	18. What is your nationality?
	Nigerian | Non-Nigerian (please specify)
Comments	4. Do you have any more comments you would like to share?
Updates	5. We have now come to the end of the study. Thank you very much for participating in the study. Would you like to learn about the outcomes of this study?

Appendix B: Descriptive statistics dependent variables

Mental model complexity of the causes of climate change				
	Nodes		Edges	
	Lagos (N)	**Lake Victoria (N)**	**Lagos (N)**	**Lake Victoria (N)**
Minimum	2	3	1	2
Maximum	11	17	40	55
Mean	5,56	7,47	13,72	9,28
Median	6	7	16	8
Standard deviation	1,14	2,67	8,07	5,36

Mental model complexity of the consequences of climate change				
	Nodes		Edges	
	Lagos (N)	**Lake Victoria (N)**	**Lagos (N)**	**Lake Victoria (N)**
Minimum	2	4	1	4
Maximum	12	18	32	68
Mean	5,89	10,8	12,11	17,1
Median	6	11	12	16
Standard deviation	1,47	3,07	7,98	7,95

Appendix C: Descriptive statistics independent variables

Gender				
	Lagos (N)	**(%)**	**Lake Victoria (N)**	**(%)**
(1) Male	122	48,8	387	72,6
(2) Female	128	51,2	146	27,4

Risk perception		
	Lagos (N)	**Lake Victoria (N)**
Minimum	1,18	1,00
Maximum	5,00	5,00
Mean	3,90	4,33
Median	4,00	4,21
Standard deviation	0,80	0,59

Age		
	Lagos (N)	**Lake Victoria (N)**
Minimum	18	18
Maximum	77	80
Mean	35,3	42,4
Median	35	40
Standard deviation	10,01	12,2

Education				
	Lagos (N)	**(%)**	**Lake Victoria (N)**	**(%)**
(1) Incomplete primary	9	3,6	98	18,3
(2) Primary	50	20,0	109	20,5
(3) Incomplete secondary	48	19,2	43	9,9
(4) Secondary	87	34,8	111	20,8
(5) College/Polytechnic	39	15,6	44	8,3
(6) Bachelor/First degree	0	0	51	9,6
(7) Postgraduate	2	0,8	32	6,0
(8) Other	15	6,0	35	6,6
Median	4		4	
Standard deviation	1.56		2.33	

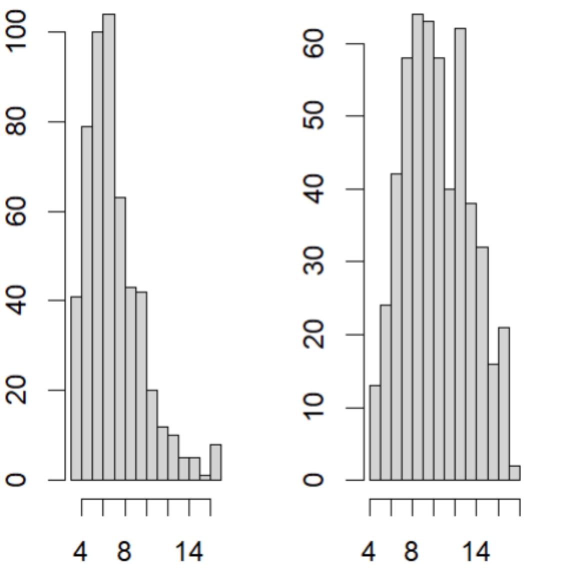
Livelihood				
	Lagos (N)		**Lake Victoria (N)**	
(1) Teaching/ Education	19	**(1) Crop Farmer**	73	
(2) Student	5	**(2) Fisher**	68	
(3) Non-governmental organization	72	**(3) Livestock keeper**	68	
(4) Business	75	**(4) Urban dweller**	103	
(5) Governmental sector	13	**(5) Urban authority/policy implementer**	96	
(6) Other	66	**(6) Scientist**	47	
		(7) Policy maker	41	
		(8) Other	37	
Median	4		4	
Standard deviation	1,47		2,05	

Appendix D: Assumptions paired T-test

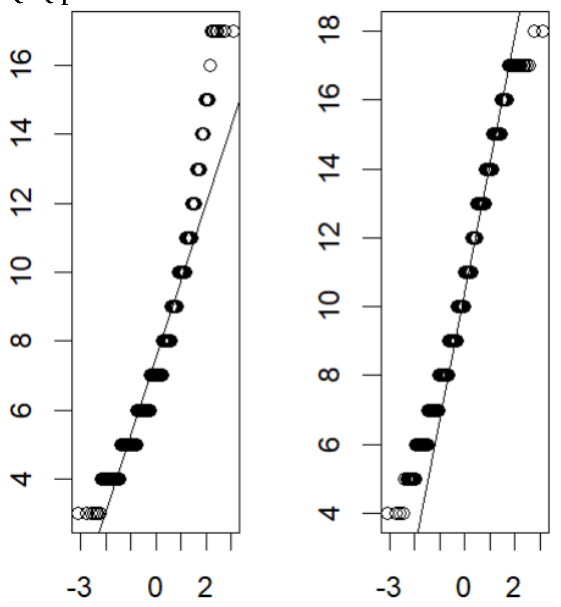
D.1: Assumptions paired T-Test MM nodes causes and nodes consequences (Lake Victoria)

1. Assumption of normality

Histogram:



Q-Q plot:



<u>→ Assumption of normality violated for 'MM nodes causes Lake Victoria'</u>

2. Assumption of equal variance:

F-test

F = 0.74995
P-value = 0.0009291

Alternative hypothesis (H1): The true ratio of variances is not equal to 1 and the groups do not have the same level of variability.

95 percent confidence interval:
0.6326255 - 0.8890415

The null hypothesis is rejected.

<u>→ Assumption of equal variance is violated</u>

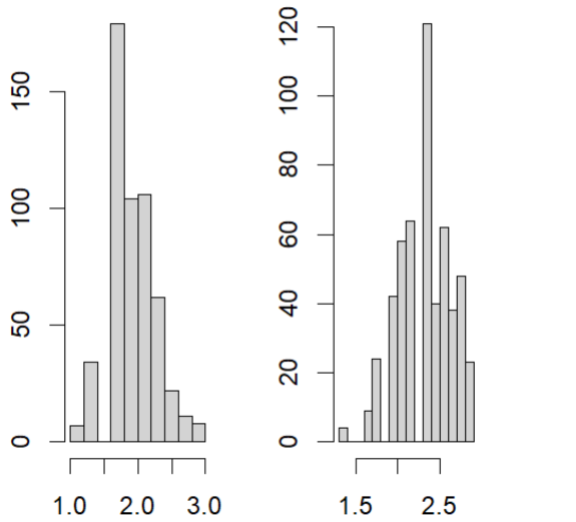
D.1: Required data transformation MM nodes causes and nodes consequences (Lake Victoria)

1: Assumption of normality for both MM causes and MM consequences

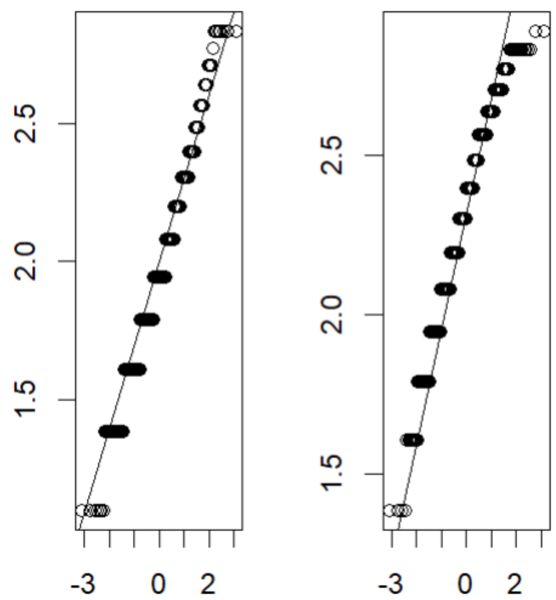
Required transformation:

MM nodes causes Lake Victoria: Original data skewed left positively, requires a logarithmic transformation
MM nodes consequences Lake Victoria: Originally data skewed left positively, requires a logarithmic transformation

Histogram after logarithmic transformation:



Q-Q plot:



→ Assumption of normality is met for MM nodes cause after logarithmic transformation, and was already met for original data nodes consequences (no improvement of normality after logarithmic transformation).

2. Assumption of equal variance:

F-test
F = 0.01204
P-value = 0.01204

Alternative hypothesis (H1): The true ratio of variances is not equal to 1 and the groups do not have the same level of variability.
95 percent confidence interval:
1.049067 - 1.474276

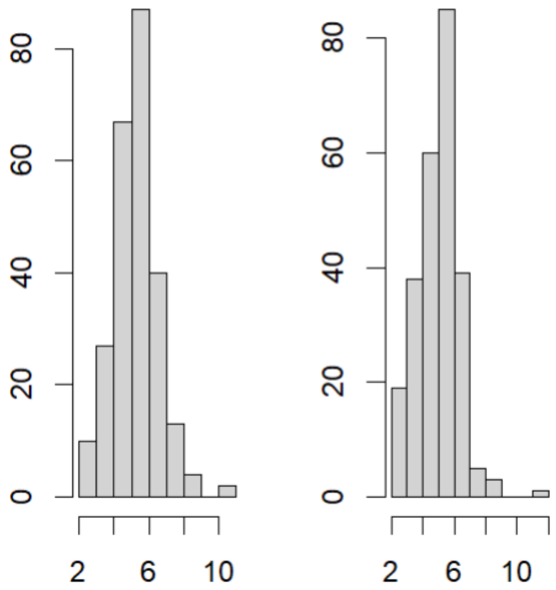
The null hypothesis is rejected.
→ Assumption of equal variance is still violated.

Assumptions Nodes Lake Victoria	
Normality	Met after 'nodes causes' logarithmic transformation.
Equal variance	Violated
Statistical test: Welch's paired T-test	

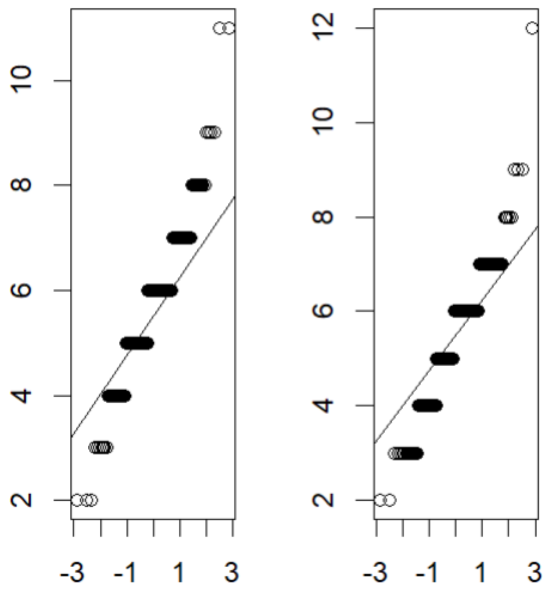
D.2: Assumptions paired T-Test MM nodes causes and nodes consequences (Lagos)

1. Assumption of normality

Histogram:



Q-Q plot:



→ Assumption of normality violated

2. Assumption of equal variance:

F-test

F = 0.99161
P-value = 0.947

Alternative hypothesis (H1): The true ratio of variances is not equal to 1 and the groups do not have the same level of variability.

95 percent confidence interval:
0.7730483 - 1.2719565

The null hypothesis is accepted

→ Assumption of equal variance is met

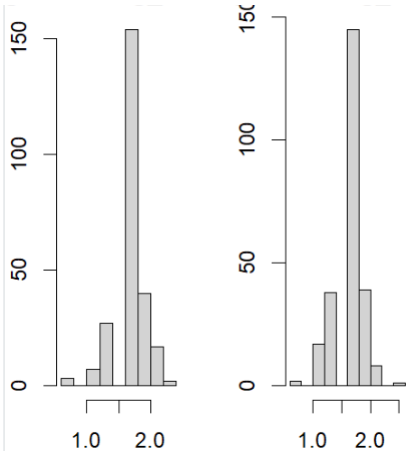
D.2: Required data transformation MM nodes causes and nodes consequences (Lagos)

1: Assumption of normality for both MM causes and MM consequences

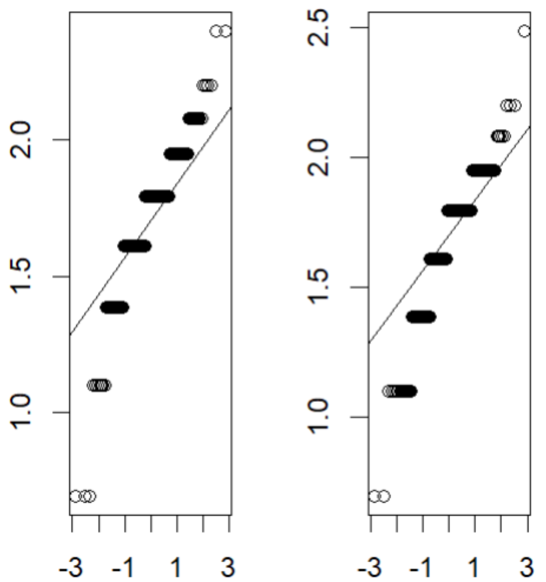
Required transformation:

MM nodes causes Lagos: Original data skewed left positively, requires a logarithmic transformation
MM nodes consequences Lagos: Originally data skewed left positively, requires a logarithmic transformation

Histogram after logarithmic transformation:



Q-Q plot:



→ Assumption of normality still violated (not improved after logarithmic transformation).

2. Assumption of equal variance:

F-test
F = 0.90682
P-value = 0.4408

Alternative hypothesis (H1): The true ratio of variances is not equal to 1 and the groups do not have the same level of variability.
95 percent confidence interval:
0.7069473 - 1.163195

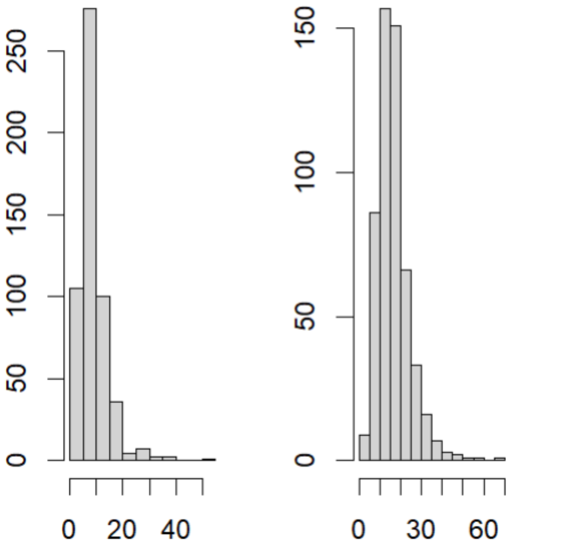
The null hypothesis is rejected.
→ Assumption of equal variance is violated with logarithmic data (not for original data)

Assumptions Nodes Lagos	
Normality	Violated (not improved after logarithmic transformation)
Equal variance	Met
Statistical test: Welch's paired T-test	

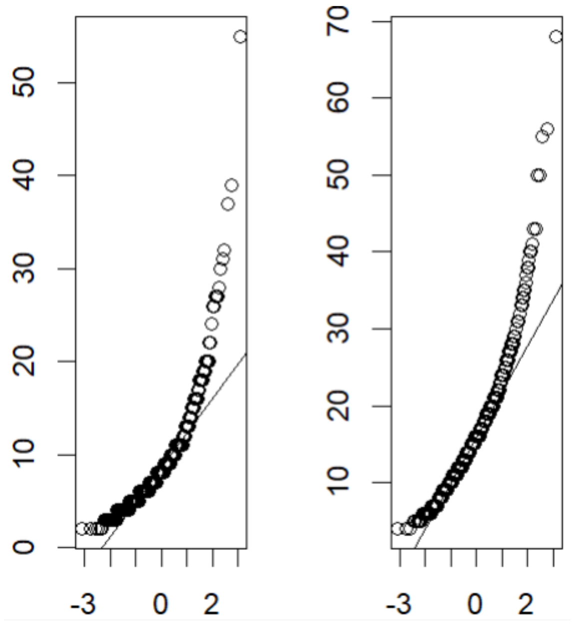
D.3: Assumptions paired T-Test MM edges causes and edges consequences (Lake Victoria)

1. Assumption of normality

Histogram:



Q-Q plot:



2. Assumption of equal variance

F = 0.45458
P-value = < 2.2e-16

Alternative hypothesis (H1): The true ratio of variances is not equal to 1 and the groups do not have the same level of variability.

95 percent confidence interval:
0.3834585 - 0.5388821

The null hypothesis is rejected.

→ Assumption of equal variance is violated

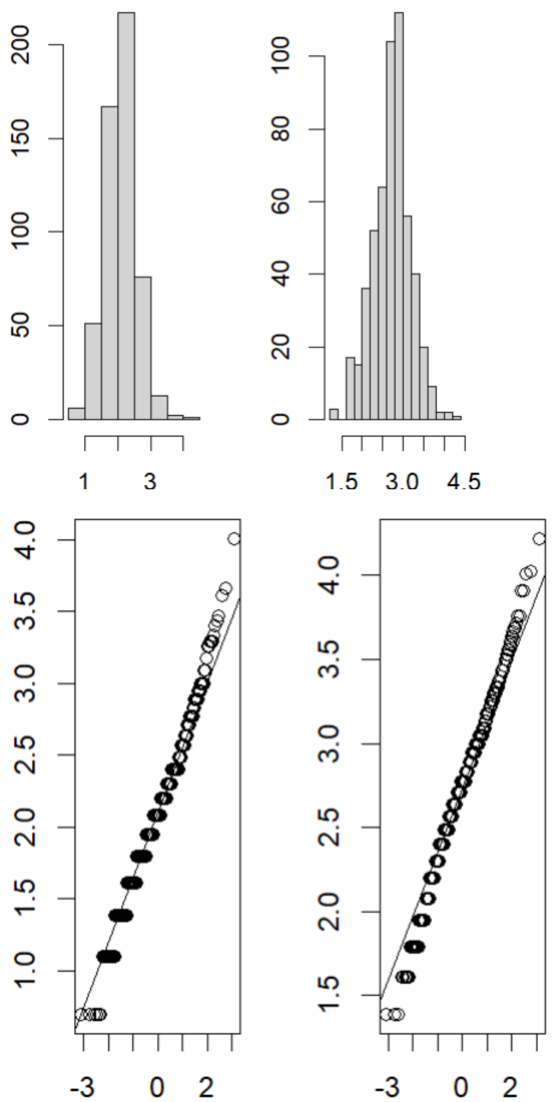
D.3: Required data transformation MM edges causes and edges consequences Lake Victoria

1: Assumption of normality for both MM causes and MM consequences

Required transformation:

Edges causes: Original data skewed left positively, requires a logarithmic transformation
Edges consequences: Originally data skewed left positively, requires a logarithmic transformation

Histogram after logarithmic transformation:



→ <u>Assumption of normality met</u>

2. Assumption of equal variance

F = 1.2313
P-value = 0.01656

Alternative hypothesis (H1): The true ratio of variances is not equal to 1 and the groups do not have the same level of variability.

95 percent confidence interval:
1.038676 - 1.459673

The null hypothesis is rejected.
→ <u>Assumption of equal variance is still violated</u>

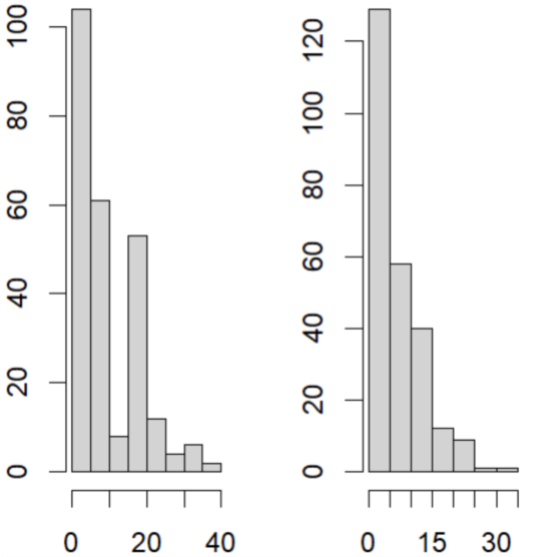
Q-Q plot after logarithmic transformation:

Assumptions Edges Lake Victoria	
Normality	Met after logarithmic transformation
Equal variance	Violated
Statistical test: Welch's paired t-test	

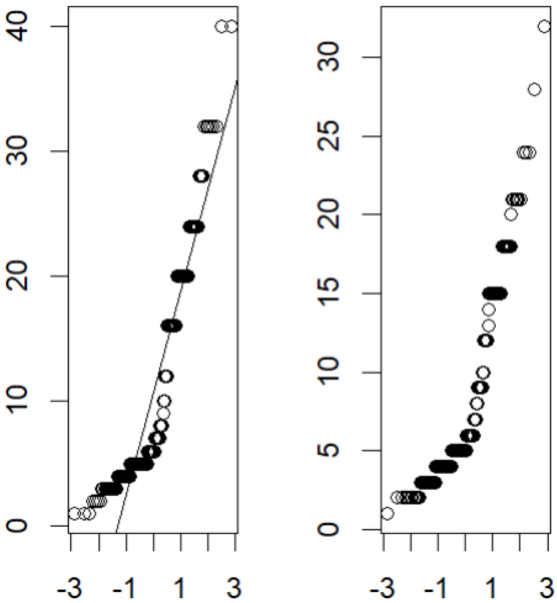
D.4: Assumptions paired T-Test MM edges causes and edges consequences (Lagos)

1. Assumption of normality

Histogram:



Q-Q plot:



Assumption of normality violated

2. Assumption of equal variance

F = 2.0562
P-value = 1.886e-08

Alternative hypothesis (H1): The true ratio of variances is not equal to 1 and the groups do not have the same level of variability.

95 percent confidence interval:
1.603017 - 2.637569

The null hypothesis is rejected.

→ Assumption of equal variance is violated

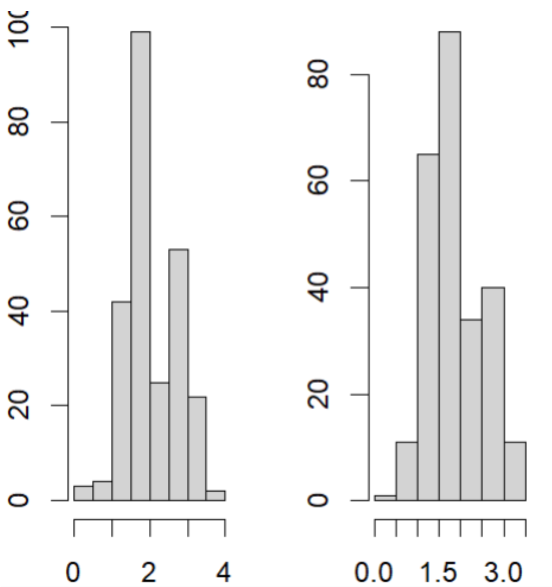
D.4: Required data transformation MM edges causes and edges consequences Lagos

1: Assumption of normality for both MM causes and MM consequences

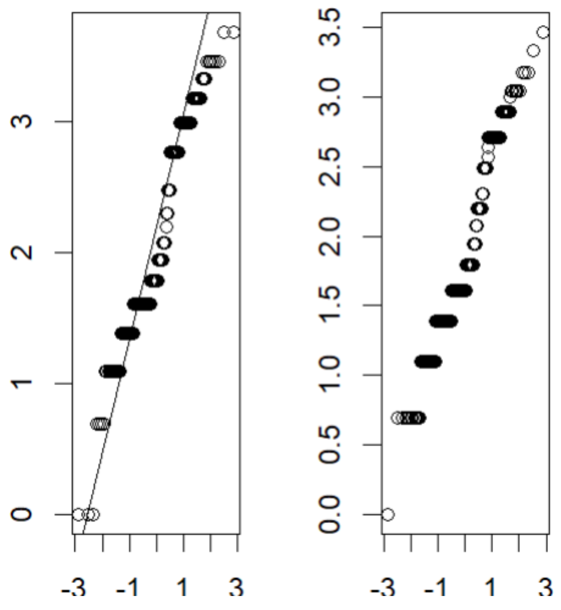
Required transformation:

Edges causes: Original data skewed left positively, requires a logarithmic transformation
Edges consequences: Originally data skewed left positively, requires a logarithmic transformation

Histogram after logarithmic transformation:



Q-Q plot after logarithmic transformation:



→ Assumption of normality still violated.

2. Assumption of equal variance

F = 1.3273
P-value = 0.02588

Alternative hypothesis (H1): The true ratio of variances is not equal to 1 and the groups do not have the same level of variability.

95 percent confidence interval:
1.034754 - 1.702561

The null hypothesis is rejected.

→ Assumption of equal variance is still violated

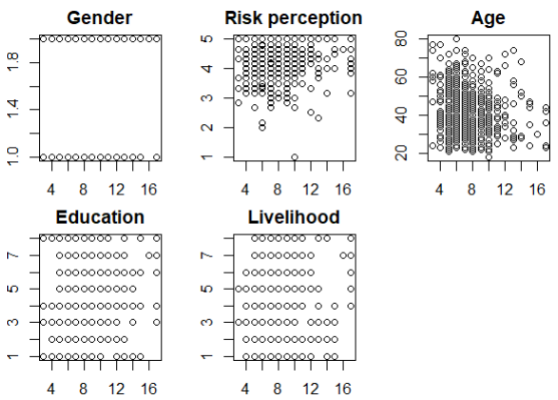
Assumptions Edges Lagos	
Normality	Violated (improved after logarithmic transformation)
Equal variance	Violated
Statistical test: Wilcoxon paired t-test	

Appendix E: Assumptions multiple linear regression

E.1 Regression model Lake Victoria Nodes Causes

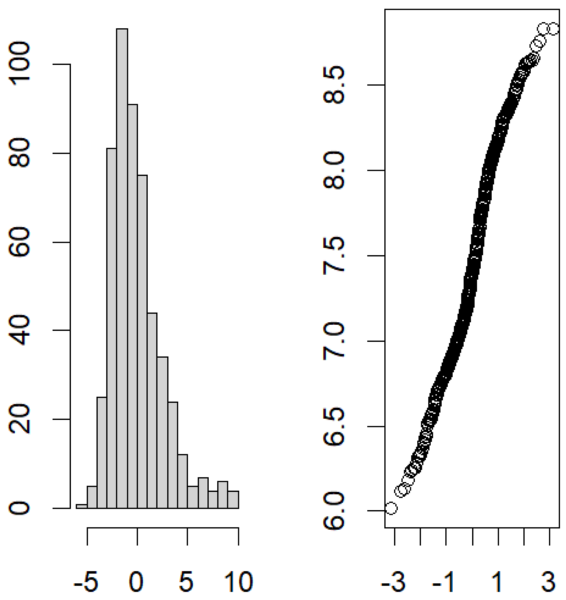
1. Assumption of linearity

(Independent variable on the y-axis 'Lake Victoria Nodes Causes on the x-axis)



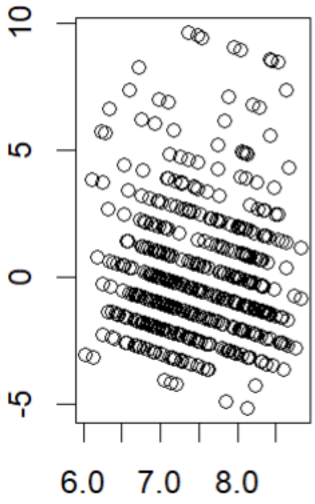
-> Assumption of linearity not violated

2. Assumption of normal distribution residuals



→ Assumption of normality met

3. Assumption of homoscedasticity residuals vs. fitted values



P-value Breusch-Pagan test: = 0.8278

→ Assumption of homoscedasticity met

4. Assumptions of no multicollinearity

Variance inflation factor (VIF) test:

Lake Victoria Nodes Causes$

Gender:	1.028000
Average Risk Perception:	1.068948
Age:	1.025134
Education:	1.059657
Livelihood:	1.106034

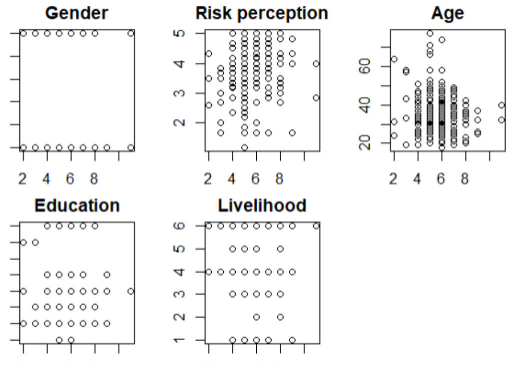
→ Assumption of no multicollinearity met

Assumptions multiple linear regression model 'Lake Victoria Nodes Causes'	
Linearity	Met
Normality	Met
Homoscedasticity	Met
No multicollinearity	Met

E.2 Regression model Lagos Nodes Causes

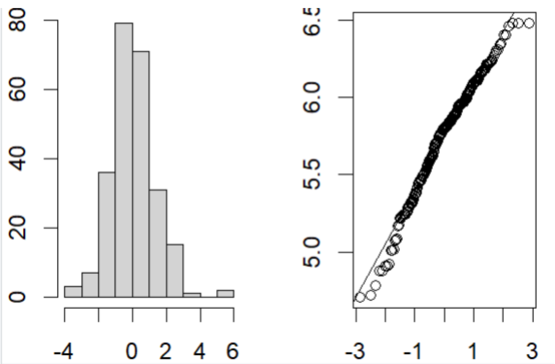
1. Assumption of linearity

(Independent variable on the y-axis 'Lagos Nodes Causes on the x-axis)



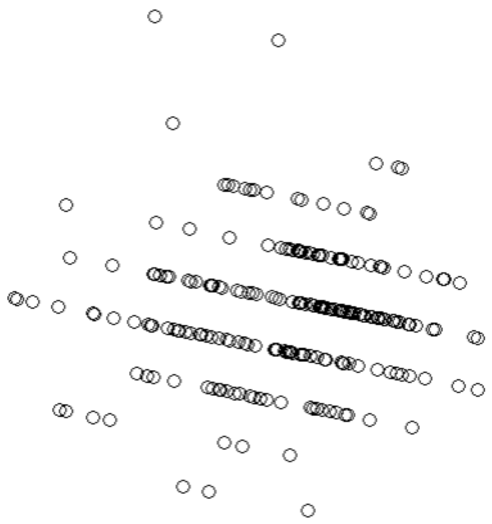
→ Assumption of linearity not violated

2. Assumption of normal distribution residuals



→ Assumption of normality met

3. Assumption of homoscedasticity residuals. fitted values



→ Assumption of homoscedasticity met

4. Assumptions of no multicollinearity

Variance inflation factor (VIF) test:

Lagos Nodes Causes$	
Gender:	1.028000
Average Risk Perception:	1.068948
Age:	1.025134
Education:	1.059657
Livelihood:	1.106304

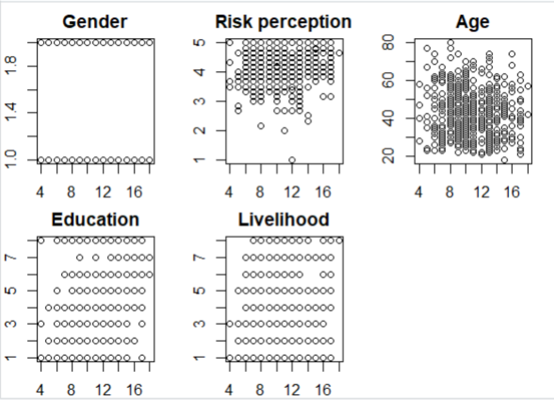
→ Assumption of no multicollinearity met

Assumptions multiple linear regression model 'Lagos Nodes Causes'	
Linearity	Met
Normality	Met
Homoscedasticity	Met
No multicollinearity	Met

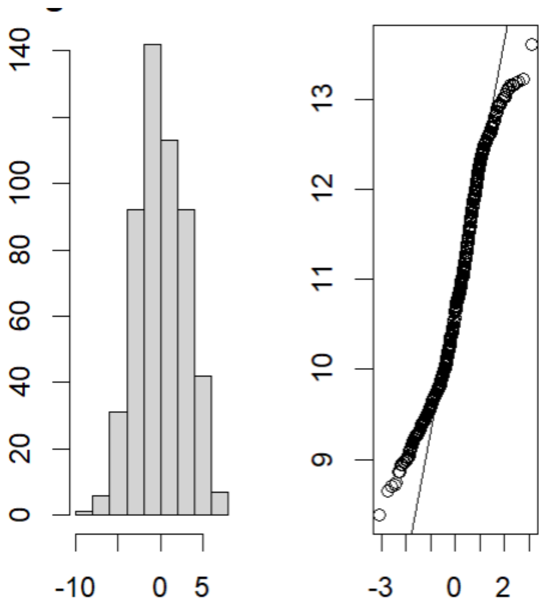
E.3 Regression model Lake Victoria Nodes Consequences

1. Assumption of linearity

(Independent variable on the y-axis, ‘Lake Victoria nodes consequences’ on the x-axis)

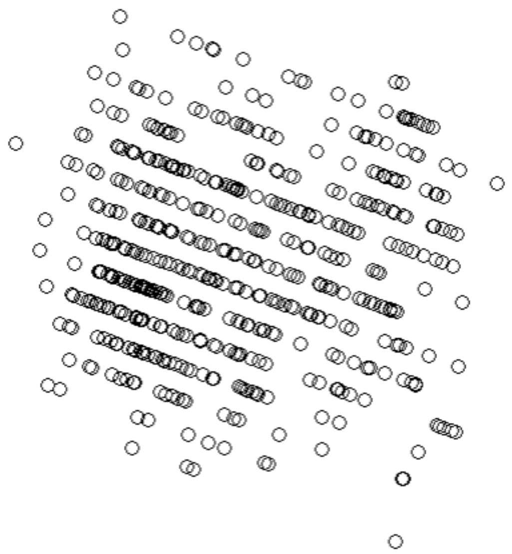


2. Assumption of normal distribution residuals



→ Assumption of normality met

3. Assumption of homoscedasticity residuals vs. fitted values



→ Assumption of homoscedasticity met

4. Assumptions of no multicollinearity

Variance inflation factor (VIF) test:

Lake Victoria Nodes Consequences$	
Gender:	1.011448
Average Risk Perception:	1.041805
Age:	1.046824
Education:	1.110482
Livelihood:	1.046702

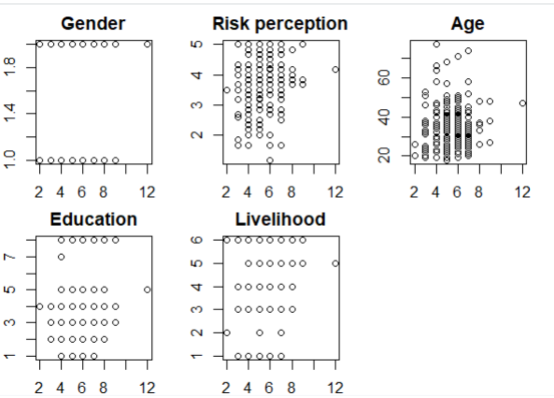
→ Assumption of no multicollinearity met

Assumptions multiple linear regression model ‘Lake Victoria Nodes Consequences’	
Linearity	Met
Normality	Met
Homoscedasticity	Met
No multicollinearity	Met

E.4 Regression model Lagos Nodes Consequences

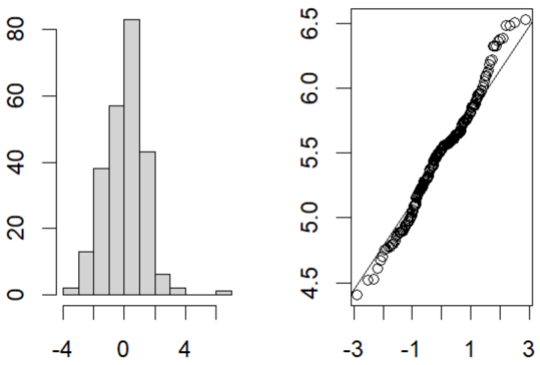
1. Assumption of linearity

(Independent variable on the y-axis 'Lagos Nodes Consequences on the x-axis)



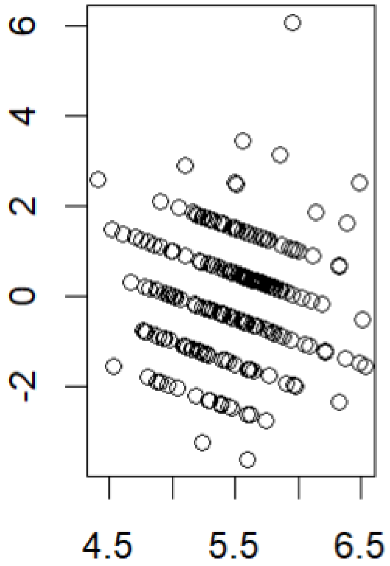
<u>→ Assumption of linearity not violated</u>

2. Assumption of normal distribution residuals



<u>→ Assumption of normality met</u>

3. Assumption of homoscedasticity residuals vs. fitted values



P-value Breusch-Pagan test: = 0.1209

<u>→ Assumption of homoscedasticity met</u>

4. Assumptions of no multicollinearity

Variance inflation factor (VIF) test:

Lagos Nodes Consequences$

Gender:	1.028000
Average Risk Perception:	1.068948
Age:	1.025134
Education:	1.059657
Livelihood:	1.106304

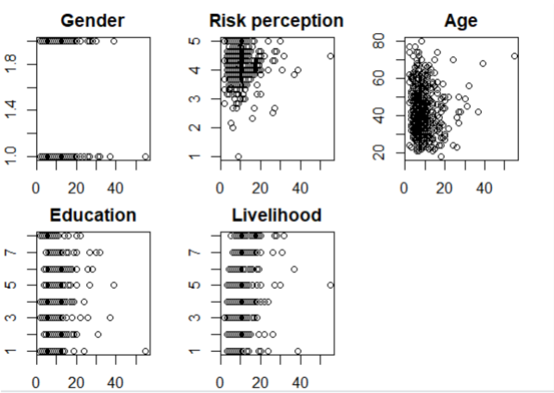
<u>→ Assumption of no multicollinearity met</u>

Assumptions multiple linear regression model 'Lagos Nodes Consequences'	
Linearity	Met
Normality	Met
Homoscedasticity	Met
No multicollinearity	Met

E.5 Regression model Lake Victoria Edges Causes

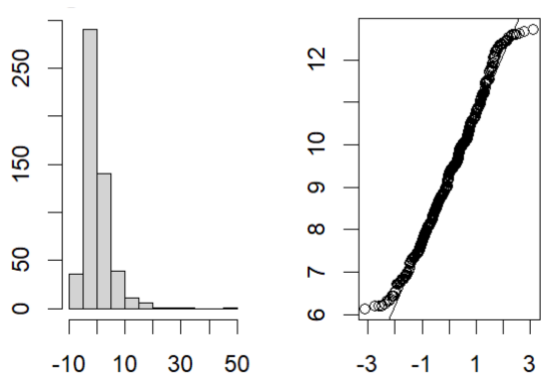
1. Assumption of linearity

(Independent variable on the y-axis ‘Lake Victoria Edges Causes on the x-axis)



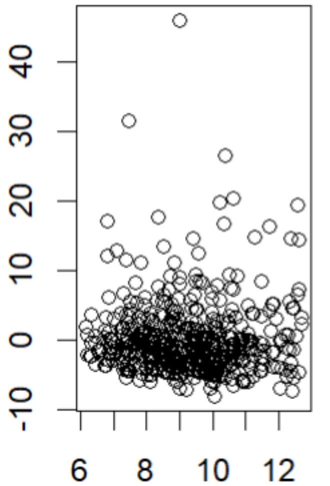
<u>-> Assumption of linearity not violated</u>

2. Assumption of normal distribution residuals



<u>→ Assumption of normality met</u>

3. Assumption of homoscedasticity residuals vs. fitted values



P-value Breusch-Pagan test: = 0.0787

<u>→ Assumption of homoscedasticity met</u>

4. Assumptions of no multicollinearity

Variance inflation factor (VIF) test:

Lake Victoria Edges Causes$

Gender:	1.011448
Average Risk Perception:	1.041805
Age:	1.046842
Education:	1.110482
Livelihood:	1.046702

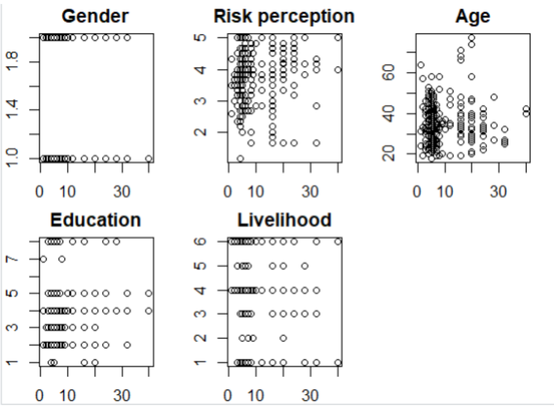
→ Assumption of no multicollinearity met

Assumptions multiple linear regression model ‘Lake Victoria Edges Causes’	
Linearity	Met
Normality	Met
Homoscedasticity	Met
No multicollinearity	Met

E.6 Regression model Lagos Edges Causes

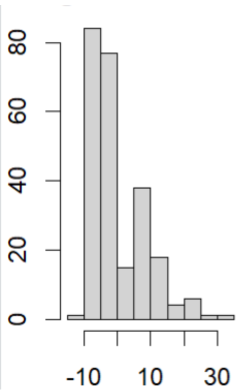
1. Assumption of linearity

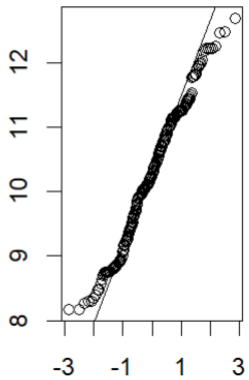
(Independent variable on the y-axis 'Lagos Edges Causes on the x-axis)



→ Assumption of linearity not violated

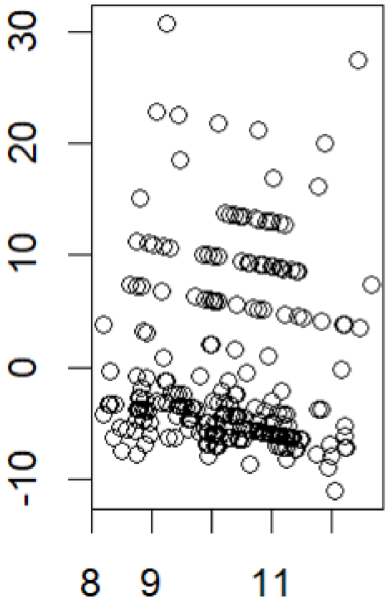
2. Assumption of normal distribution residuals





→ Assumption of normality not violated

3. Assumption of homoscedasticity residuals. fitted values



P-value Breusch-Pagan test: = 0.05699

→ Assumption of homoscedasticity met

4. Assumptions of no multicollinearity

Variance inflation factor (VIF) test:

Lagos Edges Causes$

Gender:	1.028000
Average Risk Perception:	1.068948
Age:	1.025134
Education:	1.059657
Livelihood:	1.106304

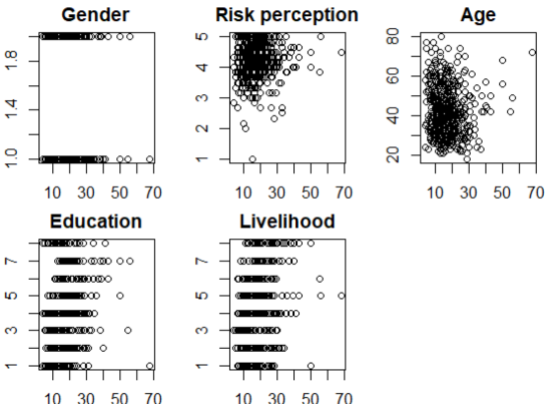
→ Assumption of no multicollinearity met

Assumptions multiple linear regression model 'Lagos Edges Causes'	
Linearity	Met
Normality	Met
Homoscedasticity	Met
No multicollinearity	Met

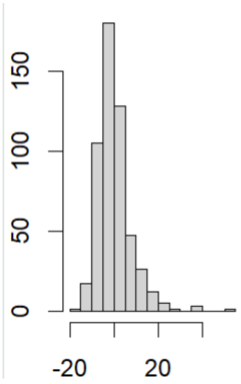
E.7 Regression model Lake Victoria Edges Consequences

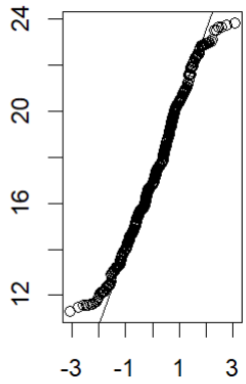
1. Assumption of linearity

(Independent variable on the y-axis, ‘Lake Victoria edges consequences’ on the x-axis)



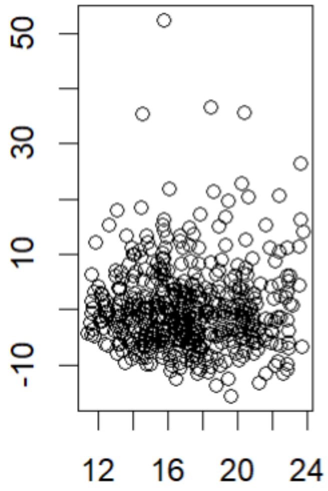
2. Assumption of normal distribution residuals





→ <u>Assumption of normality met</u>

3. Assumption of homoscedasticity residuals vs. fitted values



→ <u>Assumption of homoscedasticity met</u>

4. Assumptions of no multicollinearity

Variance inflation factor (VIF) test:

Lake Victoria Edges Consequences$

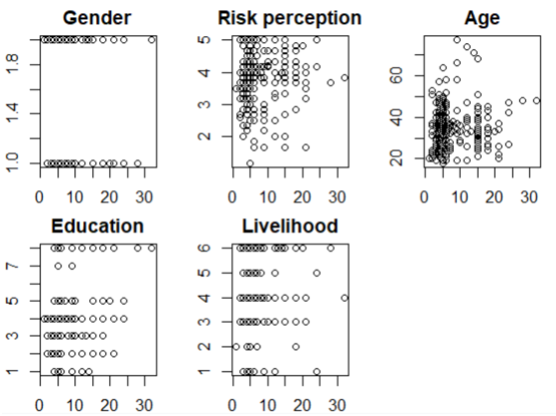
Gender:	1.011448
Average Risk Perception:	1.041805
Age:	1.046824
Education:	1.110482
Livelihood:	1.046702

→ <u>Assumption of no multicollinearity met</u>

Assumptions multiple linear regression model ‘Lake Victoria Edges Consequences’	
Linearity	Met
Normality	Met
Homoscedasticity	Met
No multicollinearity	Met

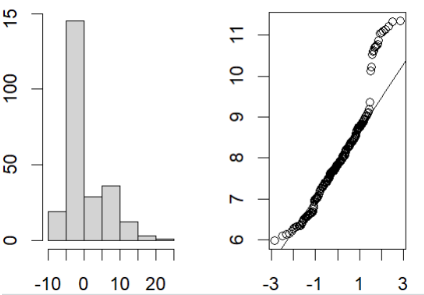
E.8 Regression model Lagos Edges Consequences

1. Assumption of linearity
(Independent variable on the y-axis 'Lagos Edges Consequences on the x-axis)



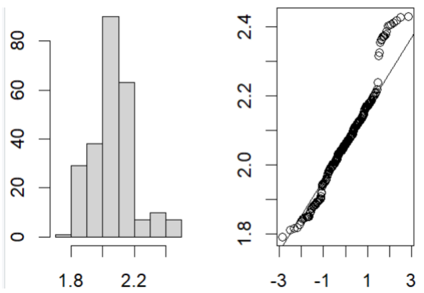
<u>→ Assumption of linearity not violated</u>

2. Assumption of normal distribution residuals



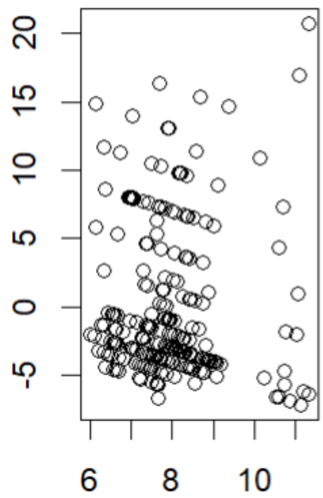
<u>→ Assumption of normality is violated</u>

Normal distribution after logarithmic transformation of Lagos Edges Consequences - Fitted Values:



<u>-> Normality met after logarithmic transformation</u>

3. Assumption of homoscedasticity residuals vs. fitted values



<u>→ Assumption of homoscedasticity met</u>

4. Assumptions of no multicollinearity

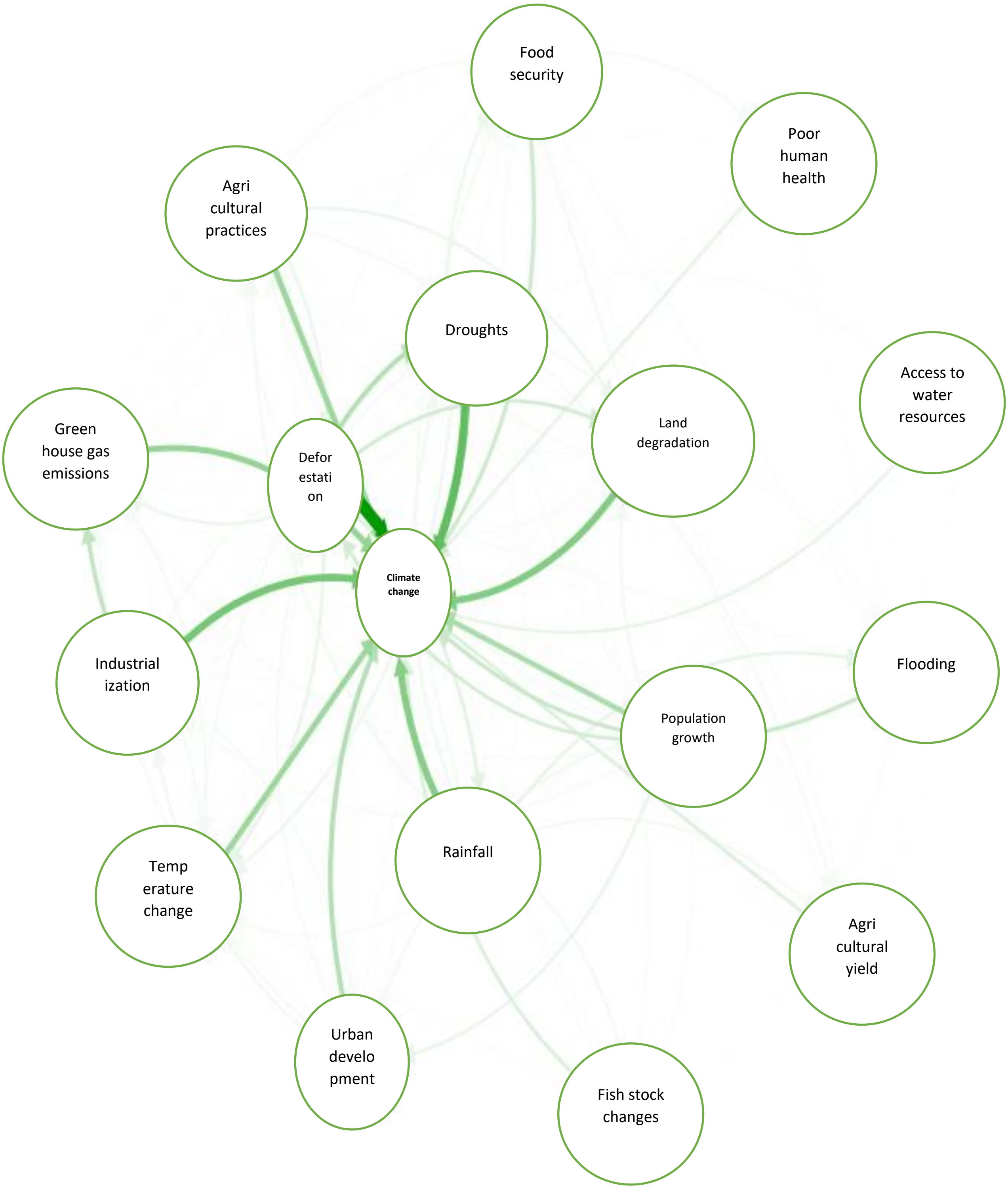
Variance inflation factor (VIF) test:

Lagos Edges Consequences$	
Gender:	1.028000
Average Risk Perception:	1.068948
Age:	1.025134
Education:	1.059657
Livelihood:	1.106304

<u>→ Assumption of no multicollinearity met</u>

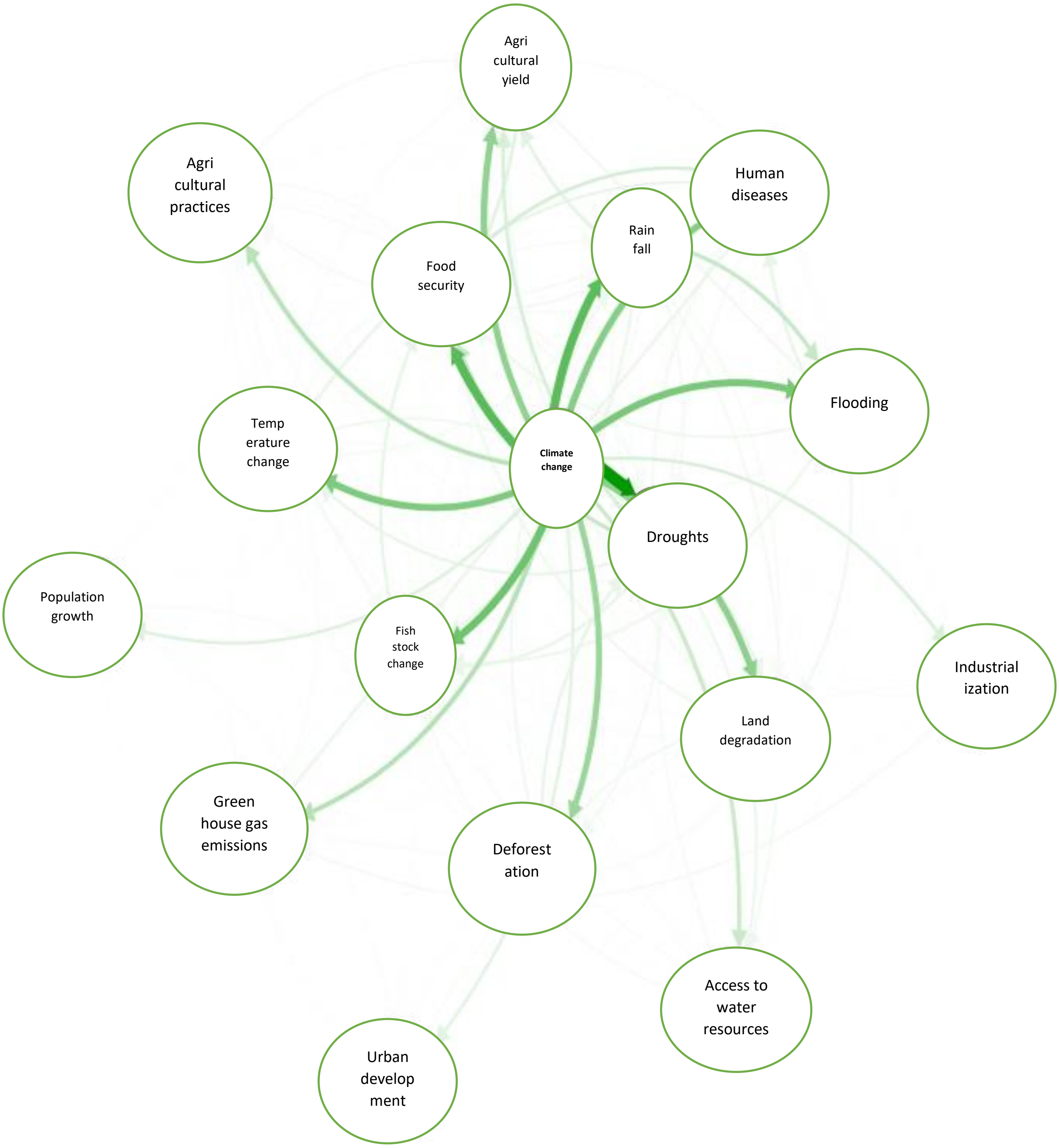
Assumptions multiple linear regression model 'Lagos Edges Consequences'	
Linearity	Met
Normality	Met after logarithmic transformation
Homoscedasticity	Met
No multicollinearity	Met

Appendix F: Aggregated Mental Model of Climate Change Causes – Lake Victoria



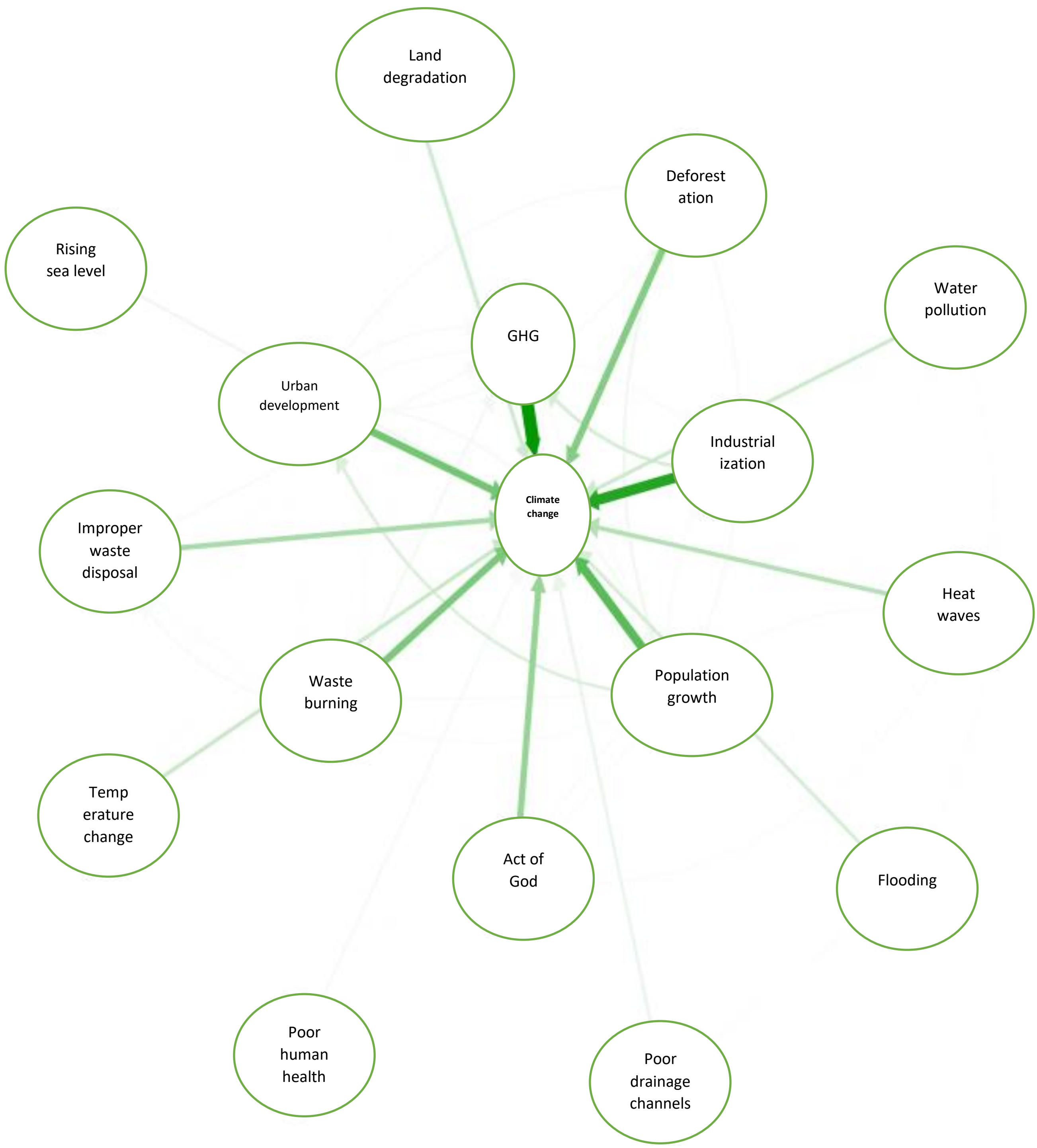
*The connections *(edges)* among concepts *(nodes)* are represented by the arrows, where the thickness of the arrows indicates the weight attributed to the connections.

Appendix G: Aggregated Mental Model of Climate Change Consequences – Lake Victoria



*The connections *(edges)* among concepts *(nodes)* are represented by the arrows, where the thickness of the arrows indicates the weight attributed to the connections.

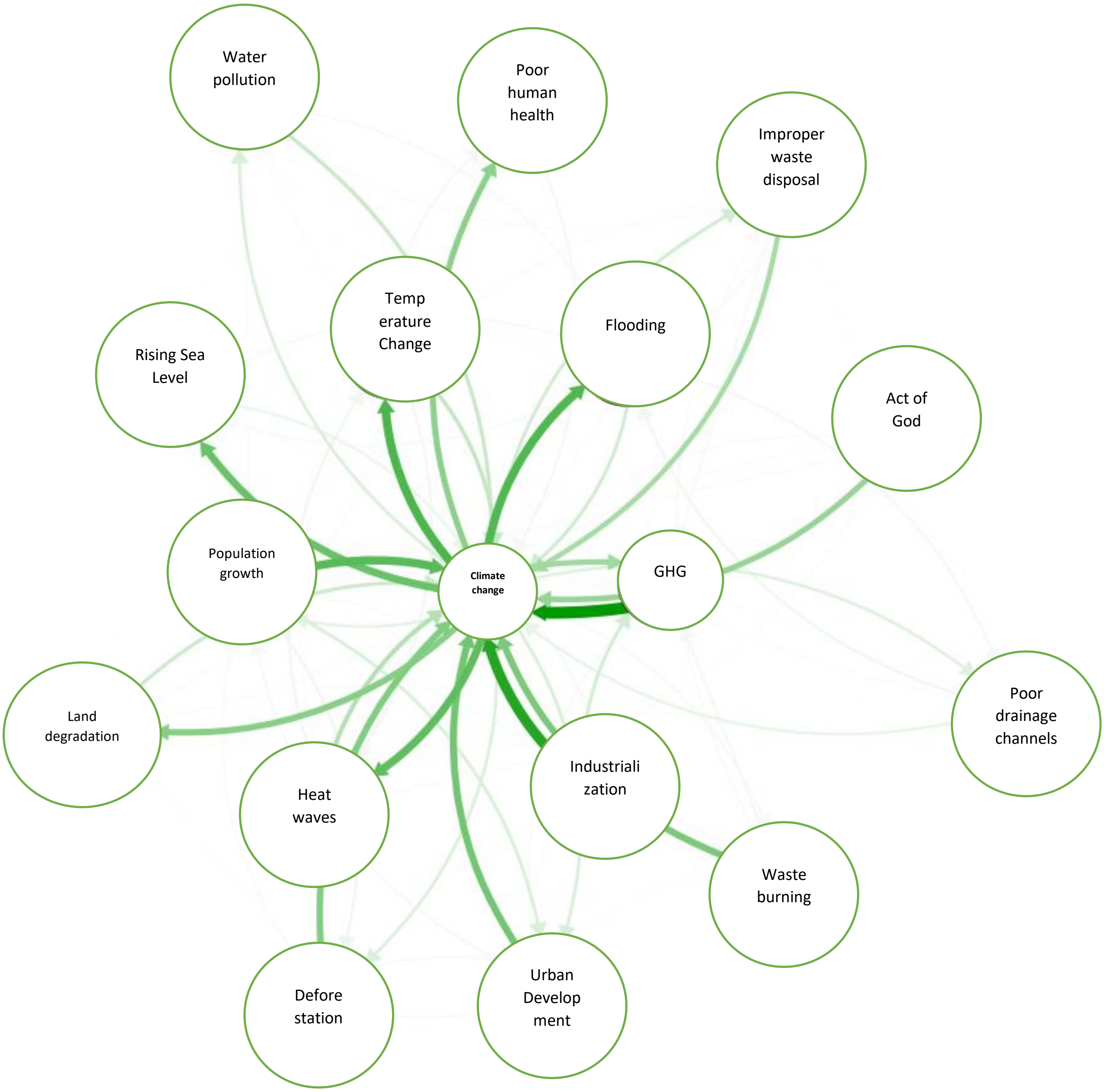
Appendix H: Aggregated Mental Model of Climate Change Causes – Lagos



* GHG = Greenhouse gas emissions

**The connections *(edges)* among concepts *(nodes)* are represented by the arrows, where the thickness of the arrows indicates the weight attributed to the connections.

Appendix I: Aggregated Mental Model of Climate Change Consequences – Lagos



* GHG = Greenhouse gas emissions
**The connections *(edges)* among concepts *(nodes)* are represented by the arrows, where the thickness of the arrows indicates the weight attributed to the connections.