Master’s Thesis

Understanding vulnerability: Climate change risk perceptions of environmental non-migrants in coastal Bangladesh

The moderating role of bonding social capital & the impact of intersectionality

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ABSTRACT

This study examines the impact of climate change risk perception on the vulnerability to climate change of environmental non-migrants (ENMs) in coastal Bangladesh while considering the effects of bonding social capital and intersectionality. A mixed methods research design, involving quantitative and geospatial data collected through surveys, and qualitative observations from conversations, was employed to gather data from 120 ENMs in five different villages in Dumuria Upazila, Bangladesh. This data included risk perceptions, vulnerability, socio-demographic characteristics, migration aspirations and capabilities, and the social context within the villages. A Climate Vulnerability Index (CVI), encompassing three dimensions – exposure, sensitivity, and adaptive capacity – was created, along with a Bonding Social Capital Index (BSCI), which included measures of community support and cohesion. The results indicate that the perceived risk of climate-induced events significantly increases the vulnerability of ENMs, contradicting prior research suggesting that higher risk perception often leads to risk response through adaptive behavior that reduces vulnerability to climate change.

The moderating role of bonding social capital on this relationship was not supported by the study, despite its projected potential to decrease vulnerability through community support. Socio-demographic characteristics and their intersection were shown to influence both risk perceptions and vulnerability. Specifically, women tended to perceive the risk of climate-induced events as lower than men. In contrast, older individuals perceived their family's chances of surviving a climate disaster as lower than younger people. Additionally, ENMs with lower education levels, lower income levels, as well as older and less educated individuals, exhibited heightened vulnerabilities.

The majority of the sample were ‘trapped’, lacking the financial or social resources to migrate despite having migration aspirations. This highlights the importance of context-specific, tailored policies for ENMs, as their vulnerabilities and risk perceptions evolve from a unique environment. This study emphasizes the need for inclusive and equitable climate change adaptation strategies that leverage local knowledge for effective disaster risk reduction. Overall, this study contributes to a more comprehensive understanding of the impacts of climate change on vulnerable communities.

Key words: environmental non-migration, climate change risk perception, climate vulnerability index, bonding social capital, intersectionality.

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BBS	Bangladesh Bureau of Statistics
BMD	Bangladesh Meteorological Department
BSCI	Bonding Social Capital Index
CVI	Climate Vulnerability Index
ENMs	Environmental Non-Migrants
GIS	Geographical Information System
IMF	International Monetary Fund
IPCC	Intergovernmental Panel on Climate Change
OLS	Ordinary-Least-Squares
UNDRR	United Nations Office for Disaster Risk Reduction

1. Introduction

The effects of human activity on the natural environment, causing rising temperatures and, consequently, global warming, directly impact the livelihoods of those in disaster-prone areas (IPCC, 2023; UNDRR, 2015). Migration is often implemented as an adaptation strategy to environmental hazards, serving as a way out when community resilience is no longer feasible (Bettini, 2017). As explained in the Sendai Framework for Disaster Risk Reduction (UNDRR, 2015), two types of migration exist: forced and voluntary. Forced migration refers to the displacement of people, while voluntary migration refers to autonomous mobility decisions (Crnceviv & Lovren, 2017; Renaud et al., 2011). Contrary to migration, deployed as a strategy to tackle the effects of environmental changes, non-migration refers to the "spatial continuity in an individual's center of gravity over a period of time'' (Mallick & Schanze, 2020; Schewel, 2019, p. 329). A non-migrant remains in their place of residence, potentially facing external risks (Naser et al., 2023).

Regarding the impacts of climate change, Mallick et al. (2023, p. 3) elaborate on the concept of environmental non-migration, as a "result of a decision-making process considering the livelihood resilience of individuals and households with their communities under threat from environmental changes". Naser et al. (2023) distinguish between voluntary and involuntary environmental non-migrants (ENMs): voluntary referring to "the people who stay voluntarily at risk" (p. 2) and do not feel trapped in the vulnerable area, and involuntary referring to people who "are not capable of handling the livelihood risks of environmental disasters yet are compelled to stay put" (p. 3).

The needs of ENMs, whether they aspire to migrate or remain and cope with environmental hazards, are often overlooked in existing international climate policies and disaster risk reduction initiatives. Policymakers often lack insight into the specific circumstances of ENMs, leading to inadequate measures in the aftermath of natural disasters (Naser et al., 2023). Nevertheless, research indicates livelihood resilience as a key driver of non-migration (Mallick et al., 2023). Resilience can be enhanced through effective adaptive behavior, influenced by the perception of climate change risks (Schewel, 2019; Wiegel et al., 2021; Zickgraf et al., 2016). Therefore, understanding how ENMs perceive the risks of environmental hazards and how these perceptions evolve, can greatly impact policymakers' ability to construct appropriate climate change adaptation frameworks.

Prior literature emphasizes the aggravation of existing vulnerabilities in the face of environmental hazards (Adger et al., 2020). However, livelihood resilience mitigates these adverse effects on the vulnerability of ENM communities (Obokata et al., 2014). Although past research has explored how physical risk and individual vulnerability shape risk perception, there is a noticeable gap in studies on the reverse effect (Brody et al., 2008). Moreover, specific research on this reverse relationship for those most affected by climate change, such as ENM communities in coastal Bangladesh, is lacking (Brody et al., 2008; Mallick, 2023). Furthermore, the ability to take risks, influenced by the perception of risk, has been identified as a driver of the livelihood resilience of vulnerable populations (Obokata et al., 2014). Thus, linking the concepts of vulnerability and climate change risk perception to ENMs, an aspect minimally explored in prior studies, can provide valuable insights into why these communities decide to stay put (Wiegel et al., 2021). Additionally, generating a more comprehensive understanding of vulnerability to climate change in Bangladesh can help the country establish livelihood-resilient practices to tackle future disasters (World Bank, 2024).

Van der Linden (2015) calls for more exhaustive research into socio-cultural factors influencing climate change risk perception. This study aims to respond by exploring the effects of bonding social capital on the relationship between risk perception and vulnerability of ENMs. Moreover, Mallick (2023) urges for an enhanced understanding of social factors shaping their non-migration behavior. Overall, combining these three concepts – vulnerability, bonding social capital, and risk perception – can yield new insights for research on ENMs, ultimately seeking a more comprehensive representation of their livelihood strategies and migration decisions.

Prior studies have addressed the importance of considering socio-demographic characteristics, such as gender and income, when analyzing attitudes and behaviors toward climate change and risk perception (Gifford & Nilsson, 2014; Van der Linden, 2015; Mallick, 2023). This study adds to those findings by assessing them in the context of ENMs in coastal Bangladesh. As climate change affects individuals unequally, impacting their vulnerability, analyzing individual characteristics is highly relevant (Adams et al., 2021). Besides, as these characteristics intersect, assessing these characteristics through an intersectional lens can provide greater insights into what shapes risk perception and vulnerability (Goodrich et al., 2019).

A geospatial mixed methods research design was deployed to study these proposed relationships, contributing to development studies by enriching the understanding of context-specific concepts, such as livelihoods and natural disasters (Harris, 2022). Quantitative and geospatial data were collected through surveys, and qualitative observations were made during conversations to analyze quantitative data. A Climate Vulnerability Index (CVI), Bonding

Social Capital Index (BSCI), and various aspects of risk perception for each survey-respondent were measured, as these concepts are highly context-specific, responding to the recommendation to establish more location-focused vulnerability indices (Ahsan & Warner, 2013). The study was conducted in five different villages within Dumuria Upazila, Khulna District, Bangladesh, selected due to the country's high susceptibility to climate change hazards, with this district being one of the most affected areas (BBS, 2021; Kumar Datta et al., 2023).

This thesis aims to bridge the mentioned gaps in the literature on the vulnerability of ENMs, their climate change risk perception, and how these two concepts interact while considering the influence of bonding social capital and the intersectionality of individual socio-demographic characteristics. Hence, the following research questions were answered:

1. *How does climate change risk perception affect the vulnerability of environmental non-migrants in hazard-prone coastal areas in Bangladesh?*
2. *How does bonding social capital moderate this relationship?*
3. *How does intersectionality affect the perception of climate change risk and the vulnerability of environmental non-migrants?*

These questions are answered in the following manner: first, the theoretical framework of this study is established by drawing on prior literature of the important concepts, such as environmental non-migration, climate change risk perception, and vulnerability. Second, hypotheses are formulated to explain the potential relationships between these concepts. Following this, the geographical contextual framework of the study is outlined, focusing on the context of Dumuria Upazila. Thereafter, the methodology of the study is detailed, with an in-depth look at the metrics used to operationalize the different concepts. Next, the results from an ordinary least squares (OLS) moderated multiple linear regression analysis, along with additional robustness checks, are presented. Lastly, these results are discussed and connected to prior literature, followed by a conclusion that includes theoretical and practical implications, limitations of the study, and recommendations for future research.

2. Theoretical framework

The theoretical framework of the study is outlined in this section. First, literature on environmental non-migration and migration aspirations and capabilities, climate change risk perception, vulnerability to climate change – consisting of the three dimensions: exposure, sensitivity and adaptive capacity – and bonding social capital is reviewed to provide a comprehensive overview of the relevant concepts used in this study. Following this review, several hypotheses are developed to explore the relationships between these factors driving climate vulnerability and mobility decisions. Finally, the analytical framework of this study is presented.

2.1 Literature review

2.1.1 Environmental non-migration

Non-migration decisions are shaped by two primary drivers: aspirations and capabilities (Carling, 2002). Mobility patterns are rooted in “people’s aspirations to migrate and their abilities to do so” (Zickgraf, 2021, p. 5). When aspirations exist but capabilities are lacking, a population can be referred to as ‘trapped’, implying involuntary non-migration. Conversely, voluntary non-migrants are characterized by the absence of aspirations to migrate but the presence of capabilities (Mallick et al., 2022; Zickgraf, 2021).

Another driver of migration decisions is the adverse effect of climate change on communities in hazard-prone areas, as it can influence their aspirations and capabilities to migrate (Mallick, 2023). Prior studies indicate that those incapable of moving are the most vulnerable to climate change impacts (Black et al., 2011; McLeman, 2017). Contrary to common beliefs, not everyone who decides to stay in their place of residence despite environmental risks does so involuntarily (Mallick & Schanze, 2011). Various factors, such as demographic characteristics, severity of environmental hazards, perceptions of risk, and economic stability, influence their non-migration decisions (Black et al., 2011; Mallick, 2023).

Nevertheless, the lack of attention given to those populations that decide to stay put has led to an underrepresentation of the needs of ENMs in policy frameworks, complicating efforts to aid in improving the livelihood resilience of those populations (Naser et al., 2023). Therefore, a deeper exploration of the drivers behind mobility decisions of both trapped and voluntary non-migrants is crucial for enhancing policy-making.

2.1.2 Climate change risk perception

Wolf & Moser (2011, p. 548) define perceptions as "views and interpretations based on beliefs and understanding". In the context of climate change, risk perception is "the process of discerning and interpreting signals from diverse sources regarding climate change, and forming a subjective judgement of the probability and severity of current or future harm associated with climate change" (Wang et al., 2021, p. 2). This definition considers how those affected perceive the risk of adverse effects of climate change. Prior research demonstrates the positive influence of perceived risk of climate change on the call-to-action for effective adaptation and mitigation measures (Frondel et al., 2017; Jakučionytė-Skodienė & Liobikienė, 2021). However, risk perceptions can differ greatly among individuals, leading to varying risk responses (Frondel et al., 2017). Previous studies identify different dimensions influencing climate change risk perception, including socio-demographic characteristics such as age, gender and education (Van der Linden, 2015; Brody et al., 2008). Therefore, perceptions differ significantly among individuals, highlighting the importance of considering these factors when analyzing behavioral responses of ENMs (Twinomuhangil et al., 2021).

2.1.3 Vulnerability to climate change

The degree of vulnerability to climate-induced disasters is influenced by geographical, environmental, and social contexts, meaning that some localities are more vulnerable than others (Adger et al., 2003). Those situated in remote, rural or more coastal areas are commonly more susceptible to climate change, increasing their vulnerability (Ali & Erenstein, 2017). The IPCC (2022, p. 43) defines vulnerability as "the propensity or predisposition to be adversely affected and encompasses a variety of concepts and elements, including sensitivity or susceptibility to harm and lack of capacity to cope and adapt". Vulnerability to climate change can be divided into three dimensions: exposure (E) to climate change, sensitivity (S) to its effects, and the capacity to adapt (AC) to climate change (IPCC, 2007; UK Aid, 2011; Yu et al., 2021). Each dimension is location-specific and contributes to the overall tendency of a population to be affected by climate change (Armah et al., 2015; Hassan, 2022). To generate a quantified assessment of an individual's or community's vulnerability to climate change, a Climate Vulnerability Index (CVI) is commonly used (Ahsan & Warner, 2013). The three dimensions previously mentioned are measured using various indicators, and the following formula is typically applied to calculate the CVI (Ahsan & Warner, 2013; Hassan, 2022):

$$Climate\ Vulnerability\ Index = \frac{(E + S + AC)}{3}$$

Exposure

A first dimension of vulnerability to climate change is the extent to which a population is exposed to environmental forces that are predicted to increase with climate change, such as temperature changes and sea level rises (Yu et al., 2021). Various international organizations have established climatic indicators of exposure, such as ‘average maximum monthly temperature’, ‘length of dry periods’ and ‘salinity of the soil’ (IMF, 2023; Hassan, 2022). The detailed method for calculating this dimension is further explained in the ‘Methodology’ section.

Sensitivity

The second dimension of vulnerability to climate change is sensitivity, referring to “the degree to which a system is affected by the climate-related stress or extreme events” (Hassan, 2022, p. 6). Sensitivity to climate change is based on factors such as ‘agricultural dependency’, ‘transport connectivity’, and important demographics (IMF, 2023; Hassan, 2022). The specific calculation method for this dimension is detailed in the ‘Methodology’ section.

Adaptive capacity

The last dimension of vulnerability covers the capacity of populations to adapt to climate change. In their analysis of climate change responses, Cinner et al. (2018) identified five key dimensions of adaptive capacity: agency, assets, flexibility, learning, and social organization. These align with Hassan’s (2022) indicators, such as ‘education availability’, ‘employment level’ and ‘basic facilities’. Adaptive capacity is context-specific, implying that each community faces different externalities that influence their behavioral responses (Armah et al., 2015). The method for calculating this dimension is explained in the ‘Methodology’ section.

2.1.4 Bonding social capital

Social capital can be conceptualized as “the nature and extent of one’s involvement in various informal networks and formal civic organizations” (Grootaert et al., 2004, p. 3). The concept emphasizes the importance of relationships (Hamilton & Lubell, 2019). A distinction can be made between bonding and bridging social capital. Bonding social capital refers to connections within the community, such as relationships with family members and neighbors. Conversely, bridging social capital pertains to connections outside the community, such as relationships with friends in different communities (Islam et al., 2020). Communities develop intangible adaptation strategies through local knowledge, which contribute to their social capital (Berman et al., 2015; Hadlos et al., 2022). Islam et al. (2020) reveal that higher social capital within a community offers greater possibilities for effective adaptation to and recovery from environmental hazards. Thus, this may affect the relationship between climate change risk perceptions and the degree of vulnerability of a community.

2.2 Hypothesis development

2.2.1 Climate change risk perception and vulnerability of ENMs

Khan et al. (2020) found that shocks and stressors caused by climate change negatively affect the vulnerability of disadvantaged groups by impacting their livelihoods. This vulnerability can be reduced by responding to climate-induced risks and developing adaptive strategies (Smit & Skinner, 2002). Moreover, the perceived severity of a climate hazard can influence a person's response efficacy, which is the degree to which they believe their adaptation strategies will have a positive outcome. Perceiving climate risks as severe may induce actions to increase livelihood resilience, thereby decreasing vulnerability (Bradley et al., 2020, Smit & Skinner, 2002). Thus, higher climate change risk perception can decrease the level of vulnerability of ENMs through adaptive risk responses. Therefore, the following hypothesized relationship between risk perception and vulnerability of ENMs is established:

H1: *Climate change risk perception has a decreasing effect on the vulnerability of ENMs.*

2.2.2 The moderating effect of bonding social capital

Building on this decreasing effect of climate change risk perception on vulnerability, assessing the facilitators of this relationship could provide a deeper understanding of its context, as both concepts are highly context-specific (Ahsan & Warner, 2013; Harris, 2022). Aldrich & Meyer (2015) highlight the importance of bonding social support during disaster adaptation. Friends and family within a close community can influence each other's attitudes and behaviors toward climate change, potentially impacting the intersection between risk perception, risk response, and vulnerability (Gifford & Nilsson, 2014; Van der Linden, 2015). Actions such as lending each other money for basic needs, helping each other during crises, and participating in communal activities can aid in reducing vulnerabilities (Islam et al., 2020). Still, Aldrich & Meyer (2015) warn that social capital may weaken during a crisis, as meaningful social connections, such as those with neighbors, may be lost. Nevertheless, in the context of perceiving and responding to climate risks, whether pre or post-disaster, bonding social capital can be employed to facilitate their effects on vulnerability. Therefore, the following hypothesis regarding the potential moderating effect of bonding social capital on the relationship between risk perception and vulnerability of ENMs is established:

H2: *Bonding social capital strengthens the negative relationship between climate change risk perception and the vulnerability of ENMs.*

2.2.3 Socio-demographic characteristics, intersectionality, and vulnerability

Prior studies have addressed the effects of age, gender, education level, and income on attitudes and behaviors toward climate change (Gifford & Nilsson, 2014; Mallick, 2023; Van der Linden, 2015). Therefore, as this study delves deeper into the effects of these attitudes and behaviors on vulnerability, assessing the role of socio-demographic characteristics is highly relevant. Climate change affects individuals unequally, impacting their vulnerability due to, among others, social conditions (Adams et al., 2021).

When examining the relationship between gender and vulnerability, prior studies have addressed the differences in climate change impacts on men and women (Goodrich et al., 2019). The unequal distribution of power, social structures, norms, and values that marginalize women, along with their underrepresentation in policy frameworks, may cause women to have less access to resources necessary to decrease vulnerability to climate change (Goodrich et al., 2017). Therefore, the following hypothesis is established:

H3a: *Gender has an increasing effect on the vulnerability of ENMs.*

Prior literature addresses that older people are more vulnerable to climate change due to weakened health conditions and greater dependency on others (Adams et al., 2021). Additionally, Mallick (2023) found that older ENMs remain in their residences more often than younger ENMs, increasing their vulnerability to climate change hazards in that area. Thus, the following hypothesis is established:

H3b: *Age has an increasing effect on the vulnerability of ENMs.*

Muttarak & Lutz (2014) argue that education enhances theoretical knowledge and practical skills, which can be utilized to gain access to vital resources and information streams. In the context of climate change, education can increase adaptive capacity and preparedness for natural hazards, this decreasing the overall vulnerability of those affected by climate change. To analyze this relationship among those who remain put, ENMs, the following hypothesis is established:

H3c: *Education has a decreasing effect on the vulnerability of ENMs.*

Previous research has found that people with lower incomes are more prone to experiencing long-term livelihood effects from climate hazards (Kessler et al., 2008). Conversely, higher income can provide increased opportunities to access resources, aiding in adaptation to climate change and reducing vulnerability (Cox & Kim, 2018; Muttarak & Lutz, 2014). To analyze this relationship among ENMs, the following hypothesis is established:

H3d: *Income has a decreasing effect on the vulnerability of ENMs.*

As socio-demographic characteristics intersect, assessing their effects through an intersectional lens can provide more significant insights into what shapes vulnerability (Goodrich et al., 2019). Versey (2020) advocates for an intersectional approach in policymaking to address differences in vulnerability to climate change. In this context, Osborne (2015, p. 133) argues that intersectionality can be defined as combinations of factors, such as ethnicity and gender, that "shape their own social position, lived experience, and thus affect vulnerability". For instance, being an older woman may have an additional increasing effect on vulnerability, while obtaining a higher education level and earning a good income can have an additional decreasing impact. Therefore, the following hypothesis is established:

H3e: *Intersectionality influences the vulnerability of ENMs.*

2.2.4 Socio-demographic characteristics, intersectionality and climate change risk perception

Previous researchers have examined the role of socio-demographic characteristics on risk perception (Brody et al., 2008; Gifford & Nilson; Van der Linden, 2015). However, studies on the intersectionality of these characteristics, or how their intersections may increase or decrease climate change risk perception, are lacking. To fully understand the potential effects of these intersections, the individual impacts of the different socio-demographic characteristics used in this study are first analyzed separately in this next section, before assessing their intersection.

Many studies discuss the differences in attitudes of men and women toward climate change and find that women often tend to perceive climate change risks as higher than men (Brody et al., 2008; Sundblad et al., 2007; Van Eck et al., 2020; Van der Linden, 2015). Moreover, some studies identify age as a predictor of climate change risk perception, with older people typically having lower risk perception (Gilbert & Lachlan, 2023; Lacroix et al., 2020). Prior literature is somewhat inconsistent regarding education level, often not finding significant effects between education and risk perception (Lacroix et al., 2020; Van der Linden, 2015). Nevertheless, Gilbert & Lachlan (2023) established that the higher the level of education, the higher the perceived risk of climate change. Lastly, van Eck et al (2020) present the negative effects of income on climate change risk perception, implying that the higher the income level, the lower the risk perception. As socio-demographic characteristics intersect, assessing the interactions between these characteristics can yield new insights valuable for climate change policymaking (Goodrich et al., 2019; Versey, 2020). Altogether, the following hypotheses have been established:

H4a: *Gender has an increasing effect on the climate change risk perception of ENMs.*

H4b: *Age has a decreasing effect on the climate change risk perception of ENMs.*

H4c: *Education has an increasing effect on the climate change risk perception of ENMs.*

H4d: *Income has a decreasing effect on the climate change risk perception of ENMs.*

H4e: *Intersectionality influences the climate change risk perception of ENMs.*

2.2.5 Environmental migration aspirations and capabilities

Non-migration decisions are influenced by migration aspirations and capabilities (Zickgraf, 2021). Prior research has established that socio-demographic characteristics and risk perceptions are driving factors of environmental non-migration (Mallick, 2023). McLeman & Gemenne (2018) stated that increasing environmental changes cause a rise in migration aspirations. Moreover, Van Praag (2021) argues for the connection between vulnerability and migration capabilities, which results in the development of migration aspirations.

However, studies on the impacts of migration aspirations and capabilities on vulnerability to climate change is minimal. Prior research emphasizes the interaction between socio-demographic characteristics, context, lived experiences, and migration aspirations, and how this interaction generates vulnerability (Gilodi et al., 2022). Therefore, this study hypothesizes the following relationships between migration aspirations, migration capabilities, and the vulnerability of ENMs:

H5a: *Migration aspirations have an increasing effect on the vulnerability of ENMs.*

H5b: *Financial resources to migrate have a decreasing effect on the vulnerability of ENMs.*

H5c: *Outside social connections to migrate have a decreasing effect on the vulnerability of ENMs.*

H5d: *The vulnerability of ENMs has an increasing effect on migration aspirations.*

Mallick (2023) found that those who perceive the risks of climate change and accept the necessity of taking risks to protect their livelihoods often do not wish to migrate. However, this study argues for the increasing effect of these risk perceptions on current migration aspirations, as perceiving a high risk of climate-induced events may cause a person to want to migrate to a safer location. Thus, the following relationship is hypothesized:

H5e: *The climate change risk perception of ENMs has an increasing effect on migration aspirations.*

2.3 Analytical framework

An analytical framework is established based on the theoretical concepts and the hypothesized relationships between the independent, moderator, control, and dependent variables. First, the model illustrates the decreasing effect of climate change risk perception on the vulnerability of ENMs (H1). Second, it presents the strengthening moderating effect of bonding social capital on this relationship (H2). Moreover, the model shows the effects of age, gender, education, income, and their intersections on the vulnerability of ENMs (H3a-e) and their effects on the climate change risk perception of ENMs (H4a-e). Finally, the model includes effects of migration aspirations and capabilities on the vulnerability of ENMs and vice versa (H5a-d), as well as the effects of climate change risk perception on migration aspirations of ENMs (H5e).

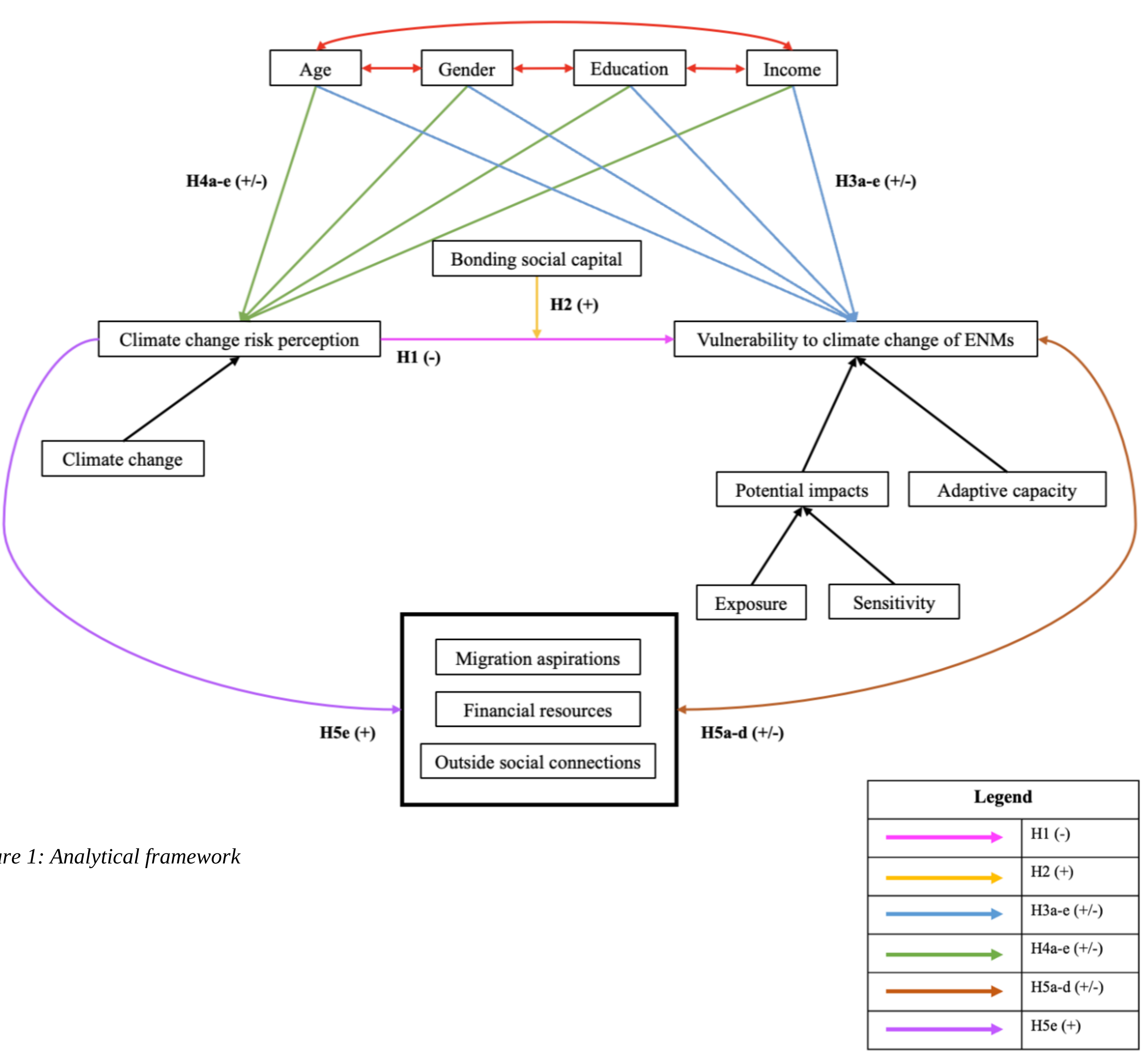

Figure 1: Analytical framework

3. Geographical contextual framework

3.1 South Asia

South Asia is afflicted by various climatic changes and natural hazards, including tropical cyclones, coastal flooding, heat waves, and urban droughts. These events significantly impact the vulnerability of South Asian populations by affecting agricultural productivity and decreasing water security. Moreover, internal environmental migration is expected to increase to 40 million climate migrants by 2050 (IPCC, 2022).

3.2 Bangladesh

Bangladesh has been chosen as the primary focus to study the effects of climate change risk perceptions on the vulnerability of environmental non-migrants (ENMs). Bangladesh ranks fifth among the most climate-vulnerable countries globally (Mallick, 2023). The geographic location of the country, predominantly situated in the Ganges Delta, significantly impacts its population (ICC Bangladesh, 2024). Natural disasters like tropical cyclones and floods frequently affect the country. Besides these rapid onset hazards, the country is also afflicted by slower onset hazards, such as rising sea levels, initiating migration patterns (IPCC, 2022). Although internal migration and displacement often occur, many studies highlight the prevalence of non-migration decisions, even when at risk of environmental hazards (Mallick, 2023; Mallick et al., 2023; Naser et al., 2023).

3.3 Khulna District

The district of Khulna is situated in the southwestern coastal part of the Bangladesh, frequently exposed to environmental hazards (BBS, 2021). According to Kabir et al. (2016), Khulna District is one of the most vulnerable areas in the country, due its proximity to the Bay of Bengal at the end of the Ganges Delta, and its low lying land area. Changes in the geophysical environment due to more extreme temperatures, impact the livelihoods of communities living in hazard-prone areas, causing aggravated vulnerabilities (Kumar Datta et al., 2023). Despite these changes, non-migration is common in this district (Mallick, 2023). Additionally, selecting this area responds to calls for an extension to other spatial areas in studies on risk perceptions and climate change (Wang et al., 2021).

3.4 Dumuria Upazila

The Disaster Prone Area Atlas (BBS, 2021) was used to identify which hazards affected the largest area and the most people in Khulna District. To ensure generalizable results, two types of hazards were selected as criteria for union selection: floods as slow onset hazards, and tropical cyclones as rapid onset hazards.

In Dumuria Upazila, the population is highly affected by floods and cyclones, impacting 279,858 people and 305,675 people, respectively (BBS, 2021). Therefore, this upazila was selected as the target area. Within this upazila, Kharnia and Shorafpur were identified as the most affected by river flooding and cyclones, leading to their selection as study areas. Shovna was established as a control union, being moderately affected by both hazards.

Different villages commonly affected by various extreme events within each target union were selected for data collection. Villages in the south of Dumuria Upazila, Kodomtola (Shovna) and Tayabpur (Shorafpur), are affected by both cyclones and river flooding. In contrast, northern villages Purbapara (Shovna), Gonali (Kharnia), and Tipna (Kharnia) are affected by cyclones and long dry periods. The two maps identifying coastal flood-prone and cyclone-prone regions in Dumuria Upazila can be found in Figure 2.

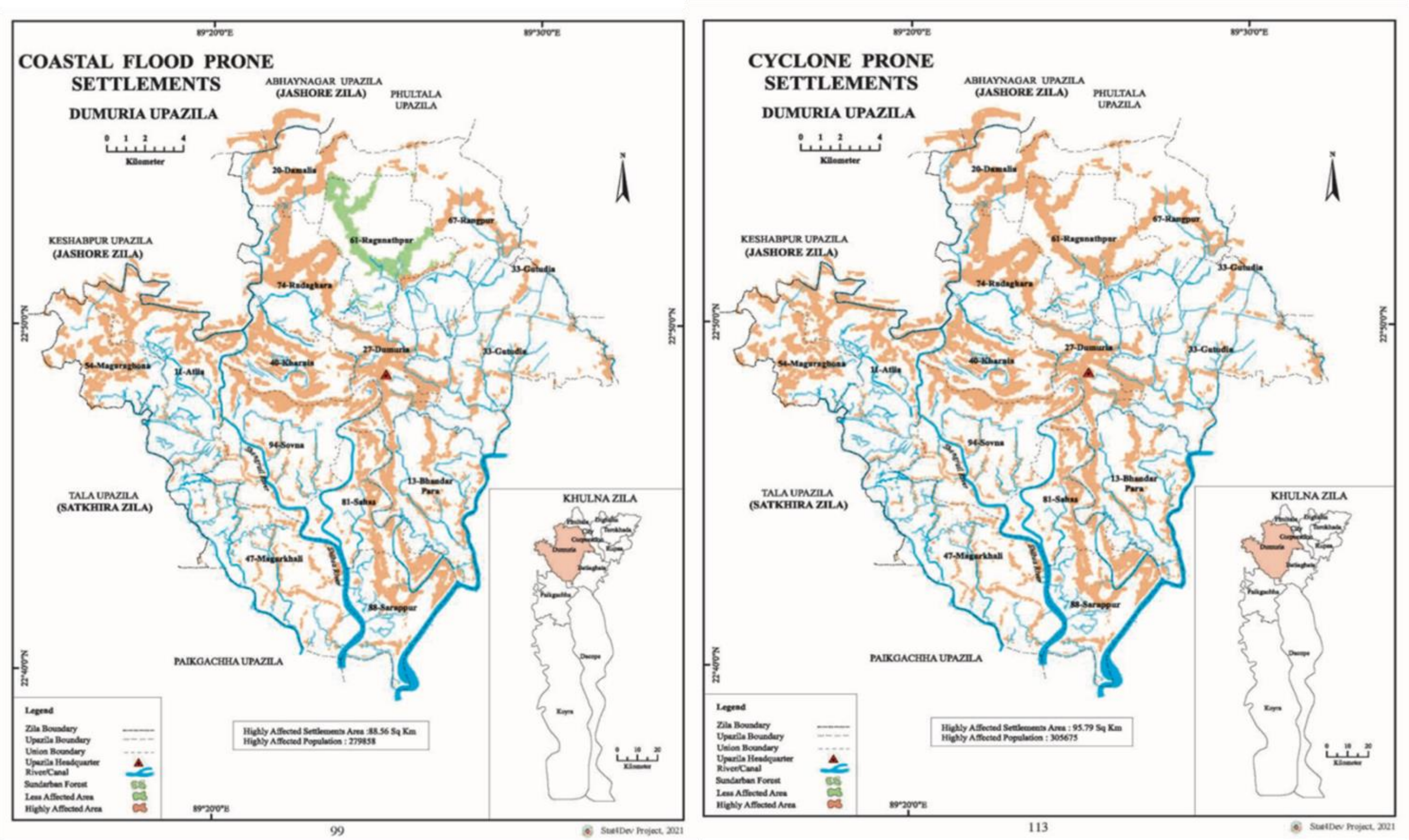

Figure 2: Coastal flood prone & cyclone prone areas in Dumuria Upazila (BBS, 2021)

3.5 Country profile

To understand the socio-economic context in which ENMs in Dumuria Upazila live, it is important to analyze Bangladesh's country profile. With a population of 171 million people, living on 133,910 km², Bangladesh is one of the most densely populated countries in the world (World Bank 2024, ICC Bangladesh, 2024). Currently, the population growth rate is 0.89% and 40.5% of the population lived in urban areas in 2023, with an annual urbanization rate of 2.88% (CIA, n.d.). The majority of the population is Muslim, followed by Hindus. Bangladesh has achieved lower-middle income status, with 5% of the population living below the international poverty line of $2.15 per capita per day. However, 30% of the population remains in moderate poverty, defined by the international moderate poverty line of $3.65 per capita per day (World Bank, n.d.). The annual GDP growth rate was 7.1% in 2022 (World Bank, 2022), contributing to the country's goal of exiting the UN's Least Developed Countries (LDC) list by 2026 (CIA, n.d.). Sheikh Hasina, the current Prime Minister of the Government of the People's Republic of Bangladesh, leads the Awami League (AL) party. She assumed office for the fifth time in January 2024, making her the world's longest-serving female Prime-Minister (Bangladesh Ministry of Foreign Affairs, n.d.; The Economist, 2023).

4. Methodology

This next section presents the research design, which forms the basis for sample selection and data collection. The operationalization of each variable is explained, after which the empirical data analysis is described, and the tested hypotheses and performed robustness checks are presented.

4.1 Research design

A geospatial mixed methods research design was deployed to conduct this study. Primary cross-sectional quantitative data and spatial data were collected through surveys, complemented by additional secondary quantitative data to execute the data analysis. Additionally, qualitative data was gathered through observations during the survey interviews, which generates a context when analyzing the dataset. Harris (2022) argues that mixed methods are relevant when studying topics such as climate change, vulnerability, and migration. Moreover, the decision to deploy this design is based on the aspired outcome of the research: reaching a larger target group, implying generalizable results, and generating a comprehensive understanding of development issues. Taghipoorreyneh & de Run (2020) emphasize the benefits of using mixed methods when aiming to understand social dimensions such as cultural values since this has the potential to improve the validity and reliability of the outcome.

A validating quantitative data model was established, where survey outcomes are the primary data source (Creswell, 2015). Combining large-scale quantitative data with spatial data and qualitative narratives provides a greater basis for justifying the results and reasons behind specific outcomes (Khatun et al., 2022). Thus, this type of design is highly relevant to this study.

4.2 Sample selection & data collection

4.2.1 Sample selection

To establish a representative sample to measure vulnerability and risk perception of ENMs within Dumuria Upazila, a non-probability sampling technique was deployed, as the sample should represent a specified group (Lamm & Lamm, 2019). Through purposive sampling, five villages, Purbapara, Kodomtola, Gonali, Tipna, and Tayabpur, from three different unions, Shovna, Kharnia, and Shorafpur, were selected as the target group. Villages in the south of Dumuria Upazila, Kodomtola, and Tayabpur, are affected by both cyclones and river flooding. On the contrary, northern villages Purbapara, Gonali, and Tipna are also affected by cyclones and long dry periods. These villages were selected to collect data from locations under different circumstances of extreme events. The study area map can be found in Figure 3.

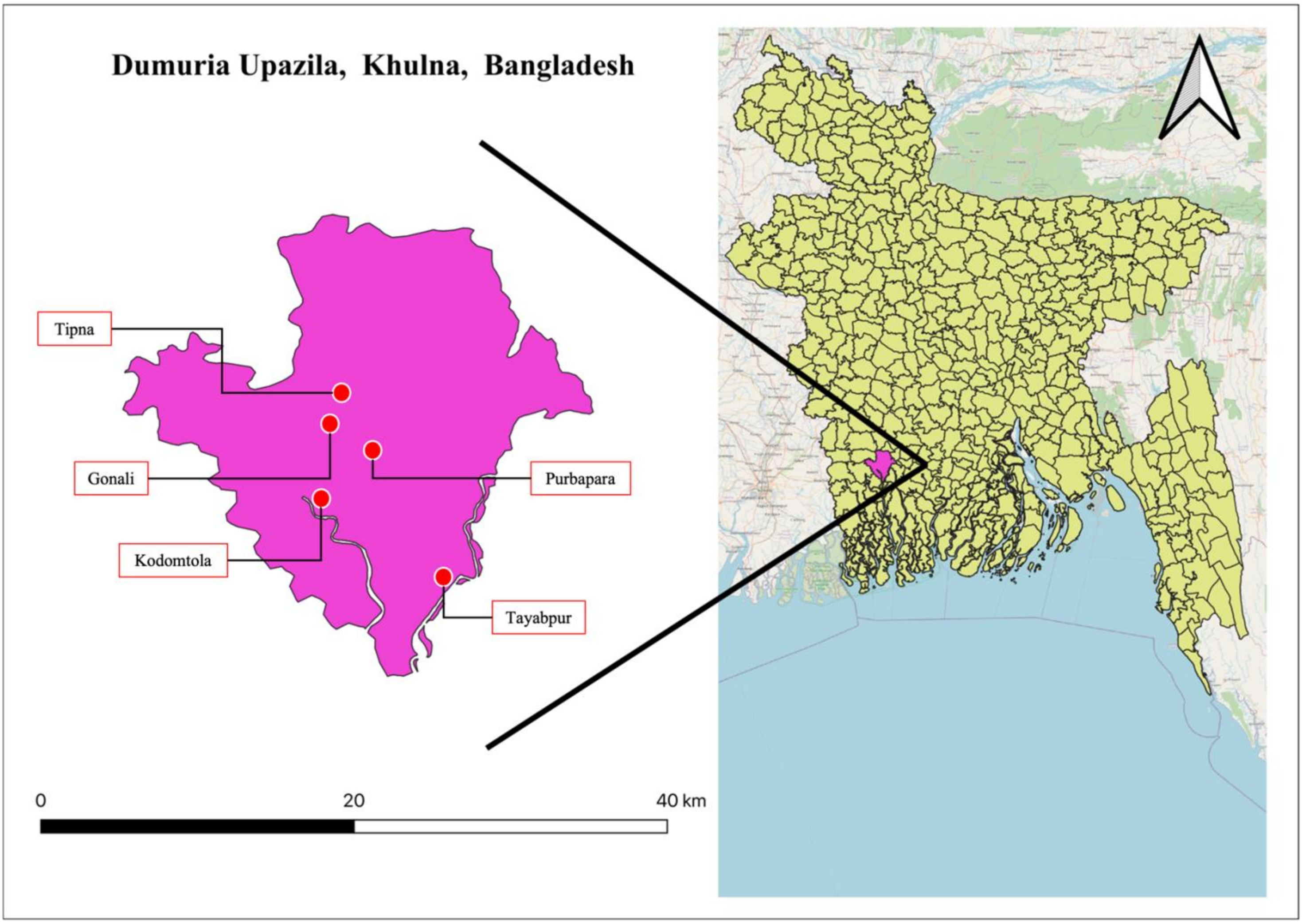

Figure 3: Study area map

Convenience sampling was used to select households in each village. Two main selection criteria were applied: the respondent had to be 18 years or older, and the respondent should know household characteristics (Mallick, 2023). To establish a significant sample size, Green's (1991) rule of thumb of $N \geq 50 + 8$ m is applied when aiming to execute a multiple regression analysis to analyze the relationship between climate change risk perception and vulnerability. Within this equation, *N* refers to the minimum sample size, and *m* indicates the collated number of independent variables, lurking and control variables, which are the 'predictor variables' altogether. Thus, this study's minimal relevant sample size, covering one dependent variable and seven predictor variables, is 114. A total of 120 households was visited to reach this sample size.

4.2.2 Primary data collection

Data was collected using the online software KoboToolbox to investigate this potential relationship. The data collection process took place in March 2024. To ensure consent to participate in this study, each participant was asked to agree with the Informed Consent Form (Appendix B). Before starting data collection, a visit was made to each Chairman's house in Shovna, Kharnia, and Shorafpur to provide them with information on the planned research activities within that union.

The survey included questions on the independent variable *climate change risk perception*, the moderator variable *bonding social capital*, and the dependent variable *vulnerability*. Moreover, questions on the control variables, such as *gender*, *age*, *education*, *income*, and *village*, were also included. To place this study in the context of environmental non-migration, *migration aspirations* and *capabilities* were also considered. The operationalization of each variable will be explained in the next section. Furthermore, the final list of questions can be found in Appendix A. Five sample surveys were conducted on the first day of fieldwork to ensure the suitability of each survey question. Subsequently, different questions were constructed for *income*, as this is a sensitive topic, and some question specifics, such as the type of livestock and type of travel vehicle, were changed.

As the target group of this study is Bengali, a research assistant from Khulna University, Bangladesh, was hired for three weeks to translate the survey questions from English to Bangla and accompany the researcher during fieldwork. After extensively going through each question with the research assistant, an employment and data agreement was signed by both the researcher and the assistant (Appendix C).

4.2.3 Secondary data collection

As explained before, secondary data was gathered to add to the primary data collected through surveys. As will be clarified in the next section regarding the operationalization of each variable, to measure *vulnerability*, multiple indicators were used, which sometimes required additional data from governmental institutions such as the Bangladesh Bureau of Statistics (BBS), the Bangladesh Meteorological Department (BMD), the Local Government Engineering Department (LGED), and the Soil Resource Development Institute (SRDI). Table 1 presents the source of each indicator of vulnerability, which will be explained in the next section.

Table 1: Indicators of vulnerability & primary and secondary sources

Variable	Category	Indicator	Source
Exposure	Climate	Average monthly maximum temperature	BMD
		Average monthly minimum temperature	BMD
		Average monthly rainfall	BMD
	Atmospheric hazards	Cyclone prone areas	BBS
		Flood-prone areas	BBS
		Drought intensity	Survey
	Land-sea hazards	Riverbank erosion	BMD
		Soil salinity	SRDI
		Groundwater salinity	SRDI
		River level rise	Survey
Sensitivity	Demography	Total population in village	BBS
		Population density in village	BBS
	Livelihood	Agricultural land	Survey
		Aquaculture	Survey
		Livestock	Survey
	Connectivity	Upazila Pucca road	LGED
		Union Pucca road	LGED
		Village Pucca road	LGED
		Upazila Kutcha road	LGED
		Union Kutcha road	LGED
		Village Kutcha road	LGED
		Distance from village to Dumuria	LGED
	Socioeconomic status	Poverty	Survey
		Agricultural dependency	Survey
Adaptive capacity	Level of education	Literacy	Survey
		Primary school in village	Survey
		Secondary school in village	Survey
	Employment type	Primary / Secondary / Tertiary	Survey
	House structure	Pucca / Semi Pucca / Kutcha House	Survey
	Road network	Pucca road	LGED
		Kutcha road	LGED
	Basic facilities	Pucca sanitation facility in household	Survey
		Electricity connection in household	Survey
		Growth center/bazar in village	Survey
		Deep tubewell water source	Survey
	Disaster response	Cyclone shelter in village	Survey
		Mobile phone user	Survey
		Internet user	Survey

4.3 Operationalization of variables

4.3.1 Independent variable – Climate change risk perception

The independent variable *climate change risk perception* is divided into four subcategories, covering topics such as perceived effects on living standard, concerns about climate change, and perceived severity of climate change (Frondel et al., 2017; Wang et al., 2021). First, answers to survey questions about climate-induced events, such as heavier rainfall, longer dry periods, cyclones and rising temperatures, were combined to assess the perceived risk of these events (Azadi et al., 2019; Brody et al., 2008; Khan et al., 2020). This variable was named *risk of climate-induced events*. Moreover, a question was posed on the concerns of a respondent towards climate change. This variable is called *concerned for climate change*. A third variable *risk for standard of living* was derived from a question about the perceived impacts of climate change on the standard of living of the respondent. Lastly, a question on the perceived *chances of family survival* in the case of a climate disaster was posed (Wang et al., 2021). Overall, 9 questions were constructed covering *climate change risk perception*, which are presented in Table 2.

Survey questions – Climate change risk perception	
Risk of climate-induced events	
1. I think that river level rises will have a negative effect on this village	1 = strongly disagree, 5 = strongly agree
2. I think that more heavy rainfall will have a negative effect on this village	1 = strongly disagree, 5 = strongly agree
3. I think that an increased number of cyclones will have a negative effect on this village	1 = strongly disagree, 5 = strongly agree
4. I think that increased surface temperatures will have a negative effect on this village	1 = strongly disagree, 5 = strongly agree
5. I think that climate change will lead to more pests and diseases in this village	1 = strongly disagree, 5 = strongly agree
6. I think that climate change will have a negative effect on the agricultural productivity of the land in this village	1 = strongly disagree, 5 = strongly agree
Concerned for climate change	
7. How concerned are you about climate change?	1 = not concerned, 5 = very concerned
Risk for standard of living	
8. I think that my standard of living will decrease due to climate change	1 = strongly disagree, 5 = strongly agree
Chances of family survival	
9. I think that my family can survive extreme weather events with good planning	1 = strongly disagree, 5 = strongly agree

Table 2: Survey questions - climate change risk perception

4.3.2 Dependent variable – Vulnerability to climate change

As explained earlier, vulnerability to climate change can be divided into three dimensions: *exposure* (E), *sensitivity* (S) and *adaptive capacity* (AC) (IPCC, 2007; UK Aid, 2011; Yu et al., 2021). Each dimension is location-specific and contributes to the overall tendency of a population to be affected by climate change (Armah et al., 2015; Hassan, 2022). To measure the extent to which a respondent is vulnerable to climate change, a *Climate Vulnerability Index (CVI)* was created, which is an accumulation of scores given to several indicators of each dimension of vulnerability. This responds to recommendations by Ahsan & Warner (2013) to develop a *CVI* focused on populations living in the coastal areas of Bangladesh, as vulnerability is extremely context and place-specific.

Several proxies established in earlier research were analyzed to decide on the specific indicators of exposure, sensitivity and adaptive capacity applicable to this study (Ahsan & Warner, 2013; Das et al., 2020; Hassan, 2022; IMF, 2023). Although most indicators can be measured individually, indicators for *exposure*, such as 'average monthly maximum temperature' are similar for all communities within Dumuria Upazila. Thus, as explained before, the *CVI* calculated in this study combines primary household data with secondary data. From different governmental databases, quantitative information was collected, specific for either Khulna Division, Khulna District, Dumuria Upazila , the three unions, or the specific villages. Again, the sources used to measure each indicator of *vulnerability* are presented in Table 1.

The calculation of the *CVI* was executed in the following manner: a score was given to each datapoint representing an indicator of the three separate dimensions, ranging from 0.2 to 1, whereafter, a collated score for each dimension was established. Different classifications of possible data points for each indicator were made based on prior studies, which can be found in Table 3 (Hassan, 2022). The lowest receivable score on a specific indicator was 0.2, as the study area is generally classified as 'vulnerable' in Bangladesh, implying a vulnerable population in any way (Hassan, 2022). The collated score for each dimension was then divided by the number of indicators within that specific dimension, which is 10 for *exposure*, 14 for *sensitivity*, and 14 for *adaptive capacity*. This ensures that each dimension has the same overall effect on the total *CVI* score, as each dimension is as important when assessing vulnerability (Ahsan & Warner, 2013; Hassan, 2022). The separate scores for each dimension were added and divided by the three dimensions. Ultimately, this score is called the CVI, ranging from a minimum of 0.2 to a maximum of 1. The following formula was used to calculate the *CVI*:

$$Climate\ Vulnerability\ Index = \frac{(E + S + AC)}{3}$$

Table 3: Classification of vulnerability scores

Variable	Category	Indicator	Very low (0.2)	Low (0.4)	Moderate (0.6)	High (0.8)	Very high (1)
Exposure	Climate	Average monthly maximum temperature (in C)	<30.25	30.25 – 30.50	30.50 – 30.75	30.75 – 31.00	>31.00
		Average monthly minimum temperature (in C)	>21.50	21.00 – 21.50	20.75 – 21.00	20.50 – 20.75	<20.50
		Average monthly rainfall (in mm)	<4.50	4.50 – 5.50	5.50 – 6.50	6.50 – 7.50	>7.50
	Atmospheric hazards	Cyclone prone area	No	-	-	-	Yes
		Flood-prone area	No	-	-	-	Yes
		Drought intensity (in months)	<1	2	3	4	>5
	Land-sea hazards	Riverbank erosion (in % of total area)	No	-	-	-	Yes
		Soil salinity (in ds/m)	<1	2 – 4	4 – 7	7 – 10	>10
		Groundwater salinity (in ds/m)	<3	3 – 6	6 – 9	9 – 12	>12
		River level rise	Decreased	-	Remained same	-	Increased
Sensitivity	Demography	Total population in village (in number)	<10000	10000 – 20000	20000 – 30000	30000 – 40000	>40000
		Population density in village (per km²)	<750	750 – 1000	1000 – 1500	1500 – 5000	>5000
	Livelihood	Agricultural land	Yes	-	-	-	No
		Aquaculture	No	-	-	-	Yes
		Livestock (in number) (0 – 20 from sample)	15 – 20>	10 – 15	5 – 10	<0 – 5	0
	Connectivity	Upazila Pucca road (in km per km²)	>0.50	0.40 – 0.50	0.30 – 0.40	0.20 – 0.30	<0.20
		Union Pucca road (in km per km²)	>0.50	0.40 – 0.50	0.30 – 0.40	0.20 – 0.30	<0.20
		Village Pucca road (in km per km²)	>0.50	0.40 – 0.50	0.30 – 0.40	0.20 – 0.30	<0.20
		Upazila Kutcha road (in km per km²)	<0.10	0.10 – 0.20	0.20 – 0.30	0.30 – 0.40	>0.40
		Union Kutcha road (in km per km²)	<0.10	0.10 – 0.20	0.20 – 0.30	0.30 – 0.40	>0.40
		Village Kutcha road (in km per km²)	<0.10	0.10 – 0.20	0.20 – 0.30	0.30 – 0.40	>0.40
		Distance from village to Dumuria (in km)	<2	2.0 – 4.0	4.0 – 6.0	6.0 – 8.0	>8
	Socioeconomic status	Poverty (below international poverty line)	No	-	-	-	Yes
		Agricultural dependency	No	-	-	-	Yes
Adaptive capacity	Level of education	Literacy (% of household)	50>	50 – 40	30 – 40	20 – 30	>20

	Primary school in village	Yes	-	-	-	No
	Secondary school in village	Yes	-	-	-	No
Employment type	Primary / Secondary / Tertiary	Tertiary	-	Secondary	-	Primary
House structure	Pucca / Semi Pucca / Kutcha house	Pucca	-	Semi Pucca	-	Kutcha
Road network	Pucca road (in km per km²)	<0.20	0.20 - 0.30	0.30 - 0.40	0.40 - 0.50	>0.50
	Kutcha road (in km per km²)	>7.0	5 - 7	3 - 5	1 - 3	<1.0
Basic facilities	Pucca sanitation facility in household	Yes	-	-	-	No
	Electricity connection in household	Yes	-	-	-	No
	Growth center/bazar in village	Yes	-	-	-	No
	Deep tubewell water source	Yes	-	-	-	No
Disaster response	Cyclone shelter in village	Yes	-	-	-	No
	Mobile phone user	Yes	-	-	-	No
	Internet user	Yes	-	-	-	No

4.3.3 Moderator variable – Bonding social capital

The moderator variable *bonding social capital* was measured by combining both the six dimensions of social capital as established by Grootaert et al. (2004), as well as relevant indicators of social networks (Das et al., 2020; Hasan, et al., 2018; Mukherjee, et al., 2019). The six dimensions of *bonding social capital* are: groups and networks, trust and solidarity, collective action and cooperation, information and communication, social cohesion and inclusion, and empowerment and political action (Grootaert et al., 2004). Moreover, some indicators of social networks are: community cohesion, relationship with neighbor, and family cohesion. These sources are combined into seven survey questions measuring *bonding social capital*. To award each respondent a score on this variable, an index was created where each answer to a question could receive a maximum score of 1. Thereafter, the scores were added up and divided by the number of questions to come to a minimum score of 0 and a maximum score of 1. The classification of each score can be found in Table 4.

To ensure the internal consistency of the *bonding social capital index (BSCI)*, Cronbach's alpha was inspected. As the number of close friends of a respondent has a value different from the answers to other questions, this indicator was deleted from the index. Then, α = 0.612, above the 'unacceptable' threshold of 0.5. The following formula was used to calculate the *BSCI*:

$$Bonding\ Social\ Capital\ Index = \frac{Indicator\ scores}{6}$$

Survey questions – Bonding social capital		
1.	How many close friends do you have?	Number (deleted)
2.	How often do people in your village help each other out when in need?	Always = 1, Never = 0.2
3.	How much do you trust the people in your village?	Totally = 1, Not at all = 0.2
4.	Would you contribute to a project in your village when it does not benefit you?	Yes = 1, No = 0
5.	Does your household participate in communal activities in the village?	Yes = 1, No = 0
6.	If you suddenly needed a small amount of money, would your neighbor be willing to give that to you?	Yes = 1, No = 0
7.	Do you ever ask your relatives or friends for advice or emotional support?	Yes = 1, No = 0

Table 4: Survey questions - bonding social capital

4.2.4 Control variables – Gender, age, education, income & village

The control variables *gender*, *age*, *education*, *income*, and *village*, were measured through different survey questions. *Education* was operationalized as the completed level of education, and *income* was measured by taking at the monthly household income. These control variables were selected as prior studies present their influence on *climate change risk perception* (Brody et al., 2008; Van der Linden, 2015). Thus, to ensure that these effects did not influence the relationship between *climate change risk perception* and *vulnerability*, they were controlled for. Moreover, the answers to the questions posed on these socio-demographic characteristics were also used to assess the effects of *intersectionality* on *risk perception* as well as *vulnerability*.

4.4 Empirical data analysis

The proposed relationships were tested through a multiple ordinary least squares (OLS) moderated linear regression analysis using StataSE 18 to analyze the data. A linear regression analysis is suitable when analyzing the relationship between continuous variables, which is the case for this study. Moreover, interaction terms were created to measure the effect of *bonding social capital* and *intersectionality* on the independent and dependent variables. The different variables were added stepwise, and the regression equation for each model can be found in Appendix J. Furthermore, geospatial data, used to assess the spatial dimension of vulnerability, was analyzed using QGIS 3.36.

4.5 Assumptions

4.5.1 Outliers

To test whether any of the variables present extreme values or outliers that might affect the outcome of the regression analyses, histograms were created for each individual variable (Appendix D). As some histograms present outliers, each variable was checked for extreme values outside of the inter-quartile range (IQR) of 1.5 (Appendix E). *Risk of climate-induced events, concerned for climate change*, *bonding social capital*, *age*, and *income* show outliers. These variables were winsorized, where outliers are replaced by less extreme values, on the lower or upper tail to minimize the effects of these outliers on the different regression models.

4.5.2 Linearity

Scatterplots were created for each variable to test the assumption of linearity (Appendix F). All scatterplots presented linear relationships between the predictor variables and the dependent variable, meaning that the assumption of linearity was met.

4.5.3 Normality

To find out if the observations for each variable are normally distributed, the Shapiro-Wilk test was performed (Appendix G). Variables with a p-value higher than 0.05 do not meet the normality assumption, which may impact the outcome of the different regression models. *Risk of climate-induced events*, *risk for standard of living*, *chances of family survival*, *village*, *financial resources to migrate*, and *outside social connections to migrate*, do not meet the assumption of normality when tested independently. Nevertheless, when performing the Shapiro-Wilk test on the multiple linear regression (Model 6), as well as the regression regarding migration aspirations & capabilities (Model 19), as a whole, and assessing whether the residuals are normally distributed, the W-statistics (0.98765; 0.980, respectively) are close to 1 and the p-values (0.34937; 0.068, respectively) are higher than 0.05, which in this case implies a normal distribution of the residuals.

4.5.4 Multicollinearity

To test the assumption of no multicollinearity, each variable's Variance Inflation Factor (VIF) was inspected (Appendix H). As each VIF is below 5, multicollinearity was absent in the data, and the assumption was not met. Still, as interaction terms were used in multiple regression, the predictor variables were mean-centered, which also addresses any signs of multicollinearity.

4.5.5 Homoskedasticity

The assumption of homoskedasticity was tested by performing the Breusch-Pagan test (Appendix I). All models present a p-value above 0.05, implying that no heteroskedasticity was detected and that the assumption was met.

4.6 Robustness check

A robustness check is performed to ensure the stability and validity of the results (Appendix J). This justifies whether the beta-coefficients and the p-values established in each regression model are correct. As multiple linear regression are performed, a bootstrapping robustness test is suitable. Bootstrapping implies that each model is resampled and refitted, in this case, 1,000 times, to assess the effects of variations in the data on the results (Wu, 1986). The models that present significant relationships in the original regression analyses, which are model 6, 8, 9, 11, 14, 16, 19, 20, 22, 23, and 25, are bootstrapped using StataSE 18. The results are presented in Appendix J, and will be discussed in the 'Results' section.

5. Results

This section presents the results derived from the quantitative dataset, the spatial data, and the additional qualitative findings. Prior to running the multiple moderated linear regression, the descriptive statistics, frequencies table, and Pearson's correlations matrix are examined. Hereafter, the regression analysis and robustness check results are included. Lastly, the geospatial results and additional qualitative findings are presented.

5.1 Secondary data for CVI calculation

Additional secondary data for calculating the CVI was collected from various governmental bodies in Bangladesh, such as the Bangladesh Meteorological Department (BMD). The findings are summarized in Table 5, which includes the data source, the location for which the data was collected, the publication year, and the corresponding data points. Often, for data needed to calculate the *exposure* dimension of *vulnerability*, the lowest geographical level for which data was available was the upazila level. Consequently, this results in the same data points being used for all respondents from Dumuria Upazila.

Table 5: Secondary data for CVI calculation

Variable	Category	Indicator & measurement	Source	Location	Year	Data
Exposure	Climate	Average monthly maximum temperature (in C)	BMD	Khulna District	2022	31.10
		Average monthly minimum temperature (in C)	BMD	Khulna District	2022	21.59
		Average monthly rainfall (in mm)	BMD	Khulna Division	2022	150.78
	Atmospheric hazards	Cyclone prone areas (in % of total area)	BBS	Dumuria Upazila	2021	21.31
		Flood-prone areas (in % of total area)	BBS	Dumuria Upazila	2021	19.70
		Drought intensity	-	-	-	-
	Land-sea hazards	Riverbank erosion (in % of total area)	BBS	Dumuria Upazila	2021	0
		Soil salinity (in ds/m)	SRDI	Dumuria Upazila	2023	3.83
		Groundwater salinity (in ds/m)	SRDI	Dumuria Upazila	2023	4.62
Sensitivity	Demography	Total population (in number)	BBS	Purbapara (Shovna)	2022	8031
			BBS	Kodomtola	2022	449
			BBS	Tipna	2022	2641
			BBS	Gonali	2022	1967
			BBS	Tayabpur	2022	976
		Population density (per km²)	BBS	Purbapara (Shovna)	2022	766.81
			BBS	Kodomtola	2022	415.54
			BBS	Tipna	2022	1175.86
			BBS	Gonali	2022	886.96
			BBS	Tayabpur	2022	1269.34
	Livelihood	Agricultural land (%)	BBS	Khulna District	2022	75.14
		Aquaculture (%)	BBS	Khulna District	2022	19.66
		Livestock (in number)	BBS	Khulna District	2022	5214627
	Connectivity	Upazila Pucca road (in km per km²)	LGED	Dumuria Upazila	2023	0.22
		Union Pucca road (in km per km²)	LGED	Dumuria Upazila	2023	0.34
		Village Pucca road (in km per km²)	LGED	Dumuria Upazila	2023	1.33
		Upazila Kutcha road (in km per km²)	LGED	Dumuria Upazila	2023	0.01

		Union Kutcha road (in km per km²)	LGED	Dumuria Upazila	2023	0.01
		Village Kutcha road (in km per km²)	LGED	Dumuria Upazila	2023	1.10
		Distance from village to Dumuria (in km)	LGED	Purbapara (Shovna)	2024	2.90
			LGED	Kodomtola	2024	10.80
			LGED	Tipna	2024	4.90
			LGED	Gonali	2024	5.30
			LGED	Tayabpur	2024	14.90
	Socioeconomic status	Poverty (%)	BBS	Khulna District	2022	14.80
		Agricultural dependency (%)	-	-	-	-
Adaptive capacity	Level of education	Literacy (in % of population)	LGED	Khulna District	2022	43.90
		Educational institutions (per 1000 population)	LGED	Khulna District	2022	1.26
	Employment type	Primary / Secondary / Tertiary (%)	-	-	-	-
	Household structure	Pucca / Semi Pucca / Kutcha House (%)	-	-	-	-
	Road network	Pucca road (in km per km²)	LGED	Dumuria Upazila	2023	1.89
		Kutcha road (in km per km²)	LGED	Dumuria Upazila	2023	1.11
	Basic facilities	Pucca sanitation facility (in % of households)	BBS	Khulna Division	2022	55.03
		Electricity connection (in % of households)	BBS	Khulna Division	2022	96.00
		Growth center (in number per km²)	-	-	-	-
		Deep tubewell water source (in % of households)	BBS	Khulna Division	2022	86.53
	Disaster response	Cyclone shelters (per 1000 population)	BBS	Khulna District	2022	0.05
		Mobile phone users (in % of population)	BBS	Khulna Division	2022	69.35
		Internet users (in % of population)	BBS	Khulna Division	2022	31.49

5.2 Descriptive statistics & frequencies

Table 6 presents the descriptive statistics of this study. The sample comprises 120 respondents, habituated in 5 different villages within Dumuria Upazila in Khulna District, Bangladesh. These 5 villages are: Purbapura in Shovna (20 respondents), Kodomtola in Shovna (20 respondents), Tipna in Kharnia (20 respondents), Gonali in Kharnia (20 respondents), and Tayabpur in Shorafpur (40 respondents).

Table 6: Descriptive statistics

Variable	Obs	Mean	Std. dev.	Min	Max
Control variables					
Gender	120	1.483	0.502	1	2
Age	120	42.616	12.540	22	80
Education	120	2.075	1.078	1	5
Household income	120	17525	9129.058	2000	80000
Village	120	3.333	1.497	1	5
Extra information					
Household size	120	4.717	1.750	2	11
Income source	120	3.425	1.570	1	8
Household expenditure	120	17908.33	14557.76	2000	150000
Belief in climate change	120	1.992	0.091	1	2
Close friends	120	4.512	2.230	0	15
Dependent variables					
Risk of climate-induced events	120	4.431	0.291	3.667	5
Rising river levels	120	4.142	0.955	1	5
Increased rainfall	120	4.375	0.581	2	5
Increased number of cyclones	120	4.550	0.516	3	5
Rising surface temperatures	120	4.542	0.500	4	5
Increased number of insects & diseases	120	4.542	0.533	3	5
Concerned for climate change	120	4.233	0.775	1	5
Risk for standard of living	120	4.467	0.501	4	5
Chances of family survival	120	3.933	0.742	2	5
Belief in climate change	120	1.992	0.091	1	2
Independent variable					
Climate Vulnerability Index (CVI)	120	0.596	0.030	0.533	0.654
Purbapara	20	0.570	0.023	0.533	0.619
Kodomtola	20	0.594	0.026	0.543	0.635

Tipna	20	0.568	0.018	0.535	0.602
Gonali	20	0.597	0.023	0.567	0.640
Tayabpur	40	0.624	0.015	0.578	0.654
Voluntary ENMs	34	0.582	0.027	0.533	0.635
Trapped ENMs	86	0.602	0.030	0.535	0.654
Exposure	120	0.691	0.050	0.560	0.720
Sensitivity	120	0.567	0.060	0.414	0.642
Adaptive capacity	120	0.531	0.060	0.371	0.686
Moderator variable					
Bonding Social Capital Index (BSCI)	120	0.826	0.168	0.300	1
Purbapara	20	0.893	0.061	0.733	0.967
Kodomtola	20	0.822	0.190	0.333	1
Tipna	20	0.895	0.143	0.333	1
Gonali	20	0.760	0.240	0.300	0.933
Tayabpur	40	0.793	0.145	0.367	0.933
Voluntary ENMs	34	0.839	0.164	0.333	1
Trapped ENMs	86	0.821	0.171	0.300	1
Close friends	120	4.512	2.230	0	15

Table 7: Frequencies

Variable	Category	Frequency	Percent (≈)
Gender	Male	62	52%
	Female	58	48%
Education	None	46	38%
	Primary school	32	27%
	Secondary school	35	29%
	Post-secondary non-tertiary school	1	1%
	Bachelor's degree or equivalent	6	5%
Income source	Sale of crops	15	13%
	Sale of livestock & products	9	8%
	Sale of fishes & fisheries	56	47%
	Shopkeeper, tea-stall owner	13	11%
	Day labor	8	7%
	Van, easy-bike, rickshaw driver	16	13%
	Formal work	2	2%
	Other	1	1%

Migration aspirations & capabilities	Have migration aspirations	86	72%
	Have financial resources to migrate	5	4%
	Have social connections to migrate	21	18%

5.2.1 Control variables

First of all, when analyzing the descriptive statistics and frequencies for the control variables and additional questions posed to create a general context of the sample, the average household size is approximately 5 persons (mean = 4.717), ranging from 2 to 11. The sample is balanced in terms of *gender*, with 51.67% of the respondents being male and 48.33% being female, as shown in Table 7. The average *age* of the respondents is approximately 43 years old (mean = 42.616), with ages ranging from 22 to 80. Most respondents have attended primary school, completing 5 years of schooling. The sample's most common form of employment is selling fish and fisheries, with household *income* ranging from 2,000 to 80,000 BDT per month. Many families have higher expenditures than *income*, leading them to take loans from NGOs or banks to maintain their standard of living. When compared to the international poverty line of $2.15 (236 BDT) per capita per day as established by the World Bank (n.d.), 95% of the sample lives in extreme poverty.

5.2.2 Migration aspirations & capabilities

Secondly, when analyzing the frequencies of *migration aspirations* and *capabilities*, 72% of the respondents aspire to migrate to a different area, but only 4% have the financial resources to do so. Additionally, only 21% of the respondents have social connections in other locations that could assist them in moving.

5.2.3 Climate Vulnerability Index

Thirdly, the *CVI* within the different villages ranges from average to above average, with scores between 0.533 and 0.654. The highest dimension of vulnerability for respondents in Dumuria Upazila is *exposure*, indicating that the climatic conditions in this area contribute most significantly to their vulnerability. Among the villages, Tayabpur's respondents are the most vulnerable to climate change (mean = 0.624), while those from Tipna are the least vulnerable (mean = 0.568). When comparing voluntary with trapped ENMs, trapped ENMs are more vulnerable to climate change than voluntary (mean = 0.602; mean = 0.582, respectively).

5.2.4 Climate change risk perception

Fourthly, when analyzing the dependent variables, the majority of the respondents agree (mean = 4.431, where 4 = agree and 5 = strongly agree) that climate-induced events have a negative effect on their livelihoods, perceiving this as a high risk. Among the different events combined to assess overall perceived risk, the increase in the number of cyclones is perceived as the most severe (mean = 4.550). Moreover, most respondents are concerned or very concerned about climate change (49% and 39%, respectively), and all respondents perceive that their standard of living has decreased due to climate change. Despite this, 76% of the respondents believe their family can survive a climate disaster.

5.2.5 Bonding social capital

Lastly, the moderator variable *bonding social capital*, measured by the *BSCI*, has an average of 0.826 out of 1, indicating high bonding social capital in this area. When comparing the average *BSCI* in the different villages, Tipna (mean = 0.895) and Purbapara (mean = 0.893) have the highest scores, while Gonali has the lowest (mean = 0.760). Moreover, voluntary ENMs have higher bonding social capital within their community than trapped ENMs (mean = 0.839; mean = 0.821, respectively). The respondents have an average of approximately 5 close friends, with a range from 0 to 15 (SD = 2.230). Additionally, 54% of respondents explain that they always help other villagers in need, and 84% state that they have great trust in their communities. Furthermore, 88% of respondents would take part in activities that do not directly benefit them, and they engage in communal activities in general. If financially able, 80% of respondents would lend money to close community members, and 59% often receive emotional support from their relatives and neighbors.

5.3 Pearson's correlation matrix

A Pearson's correlation matrix has been established in Table 8 to examine the correlations between the different variables. This matrix is particularly effective in analyzing potential effects between continuous variables, which is relevant for this multiple-moderated linear regression model (Liu et al., 2016).

First of all, the independent variables *risk of climate-induced events* (r = 0.298) and *chances of family survival* (r = 0.250) positively correlate with *CVI* at $p<0.01$. This implies that as the CVI increases by 1, these two independent variables increase by approximately 0.3. *Bonding social capital* negatively correlates with *CVI* at $p<0.01$ (r = -0.288), indicating that as the CVI increases, bonding social capital decreases. The control variables *education* (r = -0.327) and *income* (r = -0.422) also negatively correlate with *CVI* at p<0.01, meaning that an increase in the *CVI* leads to a decrease in education and income levels of the respondents. Contrarily, *migration aspirations* positively correlate with *CVI* at p<0.01 (r = 0.295); thus, as the CVI increases, migration aspirations also increase. *Financial resources to migrate* (r = -0,295) and *outside social connections to migrate* (-0.303) negatively correlate with *CVI* at p<0.01, meaning that an increase in the CVI decreases both financial resources and outside social connections for migration.

Secondly, the independent variable *chances of family survival* positively correlates with *risk of climate-induced events* at p<0.1 (r = 0.152), implying that as the perceived risk of climate-induced events increases, the perceived chances of family survival slightly increase. The control variables *gender* (r = -0.180) and *income* (r = -0.190) both negatively correlate with *risk of climate-induced events* at p<0.05, suggesting that higher perceived risk of climate-induced events is associated with being male and having a lower household income.

Thirdly, *migration aspirations* positively correlate with the independent variable *concern for climate change* at p<0.1 (r = 0.155), indicating that increased concern about climate change raises migration aspirations. Moreover, *migration aspirations* negatively correlate with *risk for standard of living* at p<0.1 (r = -0.153), suggesting that higher perceived risk of climate change for their current standard of living decreases migration aspirations. *Outside social connections to migrate* negatively correlate with *chances of family survival* at p<0.1 (r = -0.166), meaning that as perceived chances of family survival during a climate disaster increases, outside social connections to migrate reduce.

Regarding the moderator variable *bonding social capital*, *gender* negatively correlates with *bonding social capital* at p<0.05 (r = -0.205), implying that higher bonding social capital is associated with being male. *Income* positively correlates with *bonding social capital* at p<0.05 (r = 0.228), indicating that higher bonding social capital is associated with a slightly higher income. *Outside social connections to migrate* also present a positive correlation effect at p<0.1 (r = 0.193), meaning that as bonding social capital increases, outside social connections to migrate also increase.

When analyzing the control variables, *gender* and *age* (r = -0.243) negatively correlate at p<0.01, indicating that female respondents are often older in this sample. *Gender* and *education* (r = -0.207) also present negative correlations at p<0.05, suggesting that female respondents often have lower education levels. *Age* and *education* (r = -0.311) present negative correlations at p<0.01, meaning that a higher age correlates with a lower level of education.

Outside social connections to migrate positively correlate with *age* at $p<0.1$ ($r = 0.173$), implying that older respondents have more outside social connections to migrate. *Migration aspirations* ($r = 0.168$) and *financial resources to migrate* ($r = 0.167$) both present positive correlations with *income* at $p<0.1$, suggesting that as income increases, migration aspirations and financial resources to migrate also increase. Lastly, a positive correlation is presented between *financial resources* and *outside social connections to migrate* at $p<0.01$ ($r = 0.233$), meaning that greater financial resources are associated with increased outside social connections to migrate.

Table 8: Pearson's correlation matrix

Variables	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.
1. CVI	1.000												
2. Risk of climate-induced events	0.298***	1.000											
	(0.001)												
3. Concerned for climate change	-0.041	0.141	1.000										
	(0.657)	(0.124)											
4. Risk for standard of living	-0.145	0.077	0.011	1.000									
	(0.114)	(0.406)	(0.909)										
5. Chances of family survival	0.250***	0.152*	0.029	0.107	1.000								
	(0.006)	(0.098)	(0.750)	(0.245)									
6. Bonding social capital	-0.288***	0.026	-0.034	0.048	-0.006	1.000							
	(0.001)	(0.778)	(0.710)	(0.602)	(0.951)								
7. Gender	0.047	-0.180**	-0.135	-0.103	0.020	-0.205**	1.000						
	(0.610)	(0.049)	(0.141)	(0.265)	(0.832)	(0.025)							
8. Age	-0.101	-0.005	-0.014	0.106	-0.133	0.112	-0.243***	1.000					
	(0.270)	(0.959)	(0.879)	(0.247)	(0.147)	(0.225)	(0.008)						
9. Education	-0.327***	-0.032	0.071	0.059	-0.036	0.056	-0.207**	-0.311***	1.000				
	(0.000)	(0.731)	(0.438)	(0.521)	(0.698)	(0.545)	(0.023)	(0.001)					
10. Income	-0.422***	-0.190**	0.009	-0.052	0.001	0.228**	0.111	-0.050	0.104	1.000			
	(0.000)	(0.037)	(0.924)	(0.569)	(0.988)	(0.012)	(0.225)	(0.588)	(0.260)				
11. Migration aspirations	0.295***	0.085	0.155*	-0.153*	0.018	-0.058	0.090	0.031	-0.094	0.168*	1.000		
	(0.001)	(0.357)	(0.091)	(0.095)	(0.842)	(0.530)	(0.328)	(0.738)	(0.308)	(0.067)			
12. Financial resources to migrate	-0.295***	-0.207**	-0.124	0.056	-0.151	0.141	-0.118	0.029	0.141	0.167*	-0.054	1.000	
	(0.001)	(0.023)	(0.177)	(0.545)	(0.101)	(0.124)	(0.198)	(0.752)	(0.125)	(0.068)	(0.558)		
13. Outside social connections to migrate	-0.303***	-0.044	-0.061	-0.035	-0.166*	0.193**	-0.138	0.173*	0.213**	0.017	-0.051	0.233***	1.000
	(0.001)	(0.633)	(0.506)	(0.703)	(0.070)	(0.035)	(0.132)	(0.059)	(0.020)	(0.852)	(0.579)	(0.010)	

p-value in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

5.4 Regression analysis

5.4.1 Control variables

Model 1 presents the effects of the five control variables on the dependent variable, which corresponds with hypotheses 3a-d (Table 9). *Education*, *income*, and *village* all present significant effects. *Education* has a negative significant effect on *vulnerability* at $p<0.05$ (β = -0.004), supporting hypothesis 3c. *Income* has a negative significant effect on *vulnerability* at $p<0.01$ (β = -0.000), supporting hypothesis 3d. *Village* shows a positive significant effect on *vulnerability* at $p<0.01$ (β = 0.011). The remaining control variables, *gender* and *age*, present negative but insignificant effects (β = -0.001; β = 0.000, respectively), leading to the rejection of hypotheses 3a and 3b.

5.4.2 The effect of climate change risk perception on vulnerability

Hypothesis 1, which examines the relationship between *climate change risk perception*, divided into four subcategories, and *vulnerability*, is tested across Models 2 to 6 (Table 9). Model 2, tests the effect of the perceived *risk of climate-induced events* on *vulnerability*, showing a positive significant effect $p<0.05$ (β = 0.017), indicating that the *risk of climate-induced events* influences the *CVI*. This positive significant effect at $p<0.05$ is also observed in Model 6 (β = 0.017), the comprehensive regression model. Model 3 and 4 examine the effects of being *concerned for climate change* and the perceived *risk for standard of living* of ENMs on their *vulnerability*, both of which have negative but insignificant effects (β = -0.002; β = -0.003, respectively). Model 5 tests the effect of perceived *chances of family survival* on the *vulnerability* of ENMs, showing a positive insignificant effect (β = 0.003). Overall, Model 6 highlights four significant effects: the positive significant effect of *risk of climate-induced events* at $p<0.05$ (β = 0.017), the negative significant effect of *education* at $p<0.1$ (β = -0.004), the positive significant effect of *income* at $p<0.01$ (β = 0.000), and the positive significant effect of *village* at $p<0.01$ (β = 0.009). Therefore, hypothesis 1 is partially supported, specifically for the effect of the perceived *risk of climate-induced events* on *vulnerability*.

5.4.3 The moderating effect of bonding social capital

Hypothesis 2 is tested in Model 7 and 8 (Table 9), where the moderator and interaction terms are added to the original multiple regression. *Bonding social capital* by itself has an insignificant negative effect on the *vulnerability* of ENMs but shows a negative significant effect at $p<0.05$ on the relationship between *chances of family survival* and *vulnerability* (β = -0.029). Thus, hypothesis 2 is only partially supported.

5.4.4 The effect of intersectionality on vulnerability

Hypothesis 3e is tested in Models 9 and 10 (Table 10), with interaction terms added between the different socio-demographic characteristics to test whether *intersectionality* affects the *CVI*. Only the interaction term between *age* and *education* has a negative significant effect at $p<0.05$ (β = -0.0004). All other interaction terms do not significantly affect the *CVI* (Model 9). Furthermore, testing the effects of combining three control variables to test triple interaction effects also shows no significant effect (Model 10). Therefore, hypothesis 3e is only partially supported.

5.4.5 The effect of intersectionality on climate change risk perception

Hypotheses 4a-e are tested across Models 11 until 18 (Table 11 & 12). Initially, regression analyses are conducted between the different socio-demographic characteristics and the subcategories of climate change risk perception. A negative significant effect of *gender* on *risk of climate-induced events* is detected at $p<0.05$ (β = -0.110), rejecting hypothesis 4a. Moreover, a negative significant effect of *income* on *risk of climate-induced events* is found at $p<0.1$ (β = -7.22e-060) (Model 11), leading to the partial support of hypothesis 4d. Secondly, *age* presents a negative significant effect on *chances of family survival* at $p<0.1$ (β = -0.011) (Model 14), resulting in the partial support of hypothesis 4b. Other relationships the socio-demographic characteristics and the subcategories of climate change risk perception show no significant effects.

Double interaction terms are added between the socio-demographic characteristics to test whether *intersectionality* affects *climate change risk perception* (Table 12). Only the interaction between *education* and *income* has a positive significant effect at $p<0.05$ on *concern for climate change* (β = 0.000) (Model 16), leading to the partial support of hypothesis 4e. Given the minimal effects of the socio-demographic characteristics individually and double interactions, an analysis including triple interaction terms was not executed.

5.4.6 Migration aspirations & capabilities

Lastly, Hypotheses 5a-e are tested throughout Model 19 until 21 (Table 13). First of all, Model 19 shows that *migration aspirations* has a positive significant effect on the *CVI* at $p<0.01$ (β =

0.018). Moreover, *financial resources to migrate* and *outside social connections to migrate* both present a negative significant effect on the CVI at $p<0.01$ ($\beta = -0.034$; $\beta = -0.019$, respectively). Therefore, hypotheses 5a-c are accepted. Moreover, the positive significant effect of the *CVI* on *migration aspirations* at $p<0.01$ ($\beta = 4.428$) is presented in Model 20. Thus, hypothesis 5d is also accepted. Finally, hypothesis 5e is tested in Model 21, and a negative significant effect of risk for standard of living on migration aspirations is inspected at $p<0.1$ ($\beta = -0.147$). Thus, hypothesis 5e is rejected.

Table 9: Original multiple moderated linear regression analysis

CVI	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Independent variables								
Risk of climate-induced events		0.017**				0.017**	0.018**	0.020***
		(0.022)				(0.020)	(0.016)	(0.008)
Concerned for climate change			-0.002			-0.002	-0.002	-0.002
			(0.565)			(0.372)	(0.338)	(0.462)
Risk for standard of living				-0.003		-0.005	-0.005	-0.005
				(0.429)		(0.227)	(0.214)	(0.235)
Chances of family survival					0.003	0.003	0.003	0.004
					(0.233)	(0.247)	(0.209)	(0.192)
Moderator variable								
Bonding social capital index (BSCI)							-0.015	-0.014
							(0.213)	(0.266)
Interaction terms								
BSCI*Risk of climate-induced events								-0.020
								(0.679)
BSCI*Concerned for climate change								-0.013
								(0.545)
BSCI*Risk for standard of living								-0.002
								(0.927)
BSCI*Chances of family survival								-0.029**
								(0.044)
Control variables								
Gender	-0.001	0.000	-0.002	-0.002	-0.001	0.000	-0.001	-0.001
	(0.746)	(0.922)	(0.694)	(0.715)	(0.772)	(0.975)	(0.784)	(0.771)
Age	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.263)	(0.292)	(0.259)	(0.285)	(0.300)	(0.362)	(0.358)	(0.283)
Education	-0.004**	-0.004**	-0.004*	-0.004*	-0.004**	-0.004*	-0.004**	-0.004*
	(0.049)	(0.050)	(0.052)	(0.051)	(0.045)	(0.053)	(0.041)	(0.056)
Income	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Village	0.011***	0.112***	0.011***	0.010***	0.010***	0.009***	0.009***	0.009***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.610***	0.606***	0.610***	0.610***	0.611***	0.608***	0.610***	0.611***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R^2	0.536	0.558	0.538	0.539	0.542	0.570	0.576	0.593
Adjusted R^2	0.516	0.534	0.513	0.515	0.518	0.535	0.537	0.538
F	26.383***	23.734***	21.913***	22.020***	22.310***	16.202***	14.815***	10.909***
N	120	120	120	120	120	120	120	120

p-value in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Table 10: Double & triple interactions of intersectionality and CVI

CVI	Model 9
Independent variables	
Risk of climate-induced events	0.017** (0.024)
Concerned for climate change	-0.003 (0.295)
Risk for standard of living	-0.005 (0.227)
Chances of family survival	0.002 (0.442)
Interaction terms	
Gender*Age	-0.001 (0.170)
Gender*Education	-0.004 (0.441)
Gender*Income	-1.03e-06 (0.134)
Age*Education	-0.0004** (0.015)
Age*Income	7.84e-09 (0.761)
Education*Income	-1.61e-08 (0.960)
Control variables	
Gender	0.048* (0.066)
Age	0.001 (0.111)
Education	0.017 (0.170)
Income	-5.14e-07 (0.802)
Village	0.010*** (0.000)
Constant	0.511*** (0.000)
R^2	0.608
Adjusted R^2	0.552
F	10.773***
N	120

p-values in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

CVI	Model 10
Independent variables	
Risk of climate-induced events	0.022** (0.016)
Concerned for climate change	-0.003 (0.330)
Risk for standard of living	-0.010 (0.192)
Chances of family survival	0.008 (0.386)
Interaction terms	
Gender*Age*Education	0.000 (0.244)
Age*Education*Income	0.000 (0.567)
Education*Income*Gender	0.000 (0.833)
Income*Gender*Age	0.000 (0.226)
Control variables	
Gender	0.012 (0.120)
Age	0.000 (0.150)
Education	0.000 (0.456)
Income	0.000 (0.514)
Village	0.010*** (0.000)
Constant	0.547*** (0.000)
R^2	0.588
Adjusted R^2	0.538
F	11.657***
N	120

Table 11: Climate change risk perception & socio-demographic characteristics

Risk of climate-induced events	Model 11
Independent variables	
Gender	-0.110**
	(0.044)
Age	-0.002
	(0.385)
Education	-0.021
	(0.407)
Income	-7.22e-06*
	(0.076)
Constant	4.854***
	(0.000)
R^2	0.070
Adjusted R^2	0.038
F	2.17*
N	120

Risk for standard of living	Model 13
Independent variables	
Gender	-0.048
	(0.631)
Age	0.005
	(0.242)
Education	0.043
	(0.373)
Income	-4.06e-06
	(0.590)
Constant	4.301***
	(0.000)
R^2	0.026
Adjusted R^2	-0.008
F	0.76
N	120

Concerned for climate change	Model 12
Independent variables	
Gender	-0.209
	(0.165)
Age	-0.002
	(0.708)
Education	0.019
	(0.785)
Income	2.35e-06
	(0.834)
Constant	4.576***
	(0.000)
R^2	0.022
Adjusted R^2	-0.012
F	0.64
N	120

Chances of family survival	Model 14
Independent variables	
Gender	-0.066
	(0.659)
Age	-0.011*
	(0.091)
Education	-0.069
	(0.331)
Income	9.48e-07
	(0.932)
Constant	4.626***
	(0.000)
R^2	0.026
Adjusted R^2	-0.008
F	0.77
N	120

p-values in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Table 12: Interaction effects of intersectionality & climate change risk perception

Risk of climate-induced events	**Model 15**
Independent variables	
Gender	-0.775**
	(0.018)
Age	-0.010
	(0.334)
Education	-0.001
	(0.995)
Income	-0.000
	(0.361)
Interaction terms	
Gender*Age	0.009
	(0.113)
Gender*Education	0.077
	(0.200)
Gender*Income	8.71e-06
	(0.320)
Age*Education	-0.003
	(0.184)
Age*Income	8.45e-08
	(0.802)
Education*Income	1.35e-07
	(0.974)
Constant	5.626***
	(0.000)
R^2	0.147
Adjusted R^2	0.069
F	1.88
N	120

Risk for standard of living	**Model 17**
Independent variables	
Gender	0.545
	(0.376)
Age	0.034*
	(0.093)
Education	0.138
	(0.659)
Income	-0.000
	(0.507)
Interaction terms	
Gender*Age	-0.014
	(0.165)
Gender*Education	-0.126
	(0.271)
Gender*Income	0.000
	(0.351)
Age*Education	-0.002
	(0.583)
Age*Income	-2.44e-07
	(0.704)
Education*Income	8.89e-06
	(0.258)
Constant	3.400***
	(0.005)
R^2	0.069
Adjusted R^2	-0.017
F	0.80
N	120

Concerned for climate change	**Model 16**
Independent variables	
Gender	-0.300
	(0.739)
Age	0.007
	(0.821)
Education	0.085
	(0.852)
Income	-0.000*
	(0.069)
Interaction terms	
Gender*Age	-0.005
	(0.716)
Gender*Education	-0.153
	(0.364)
Gender*Income	0.000
	(0.128)
Age*Education	-0.007
	(0.217)
Age*Income	6.88e-07
	(0.465)
Education*Income	0.000**
	(0.033)
Constant	5.586***
	(0.000)
R^2	0.090
Adjusted R^2	0.007
F	1.08
N	120

Chances of family survival	**Model 18**
Independent variables	
Gender	0.731
	(0.429)
Age	0.016
	(0.601)
Education	0.457
	(0.330)
Income	0.000
	(0.642)
Interaction terms	
Gender*Age	-0.009
	(0.572)
Gender*Education	-0.126
	(0.463)
Gender*Income	-0.000
	(0.624)
Age*Education	-0.006
	(0.295)
Age*Income	-1.34e-07
	(0.889)
Education*Income	-5.67e-06
	(0.630)
Constant	2.708
	(0.134)
R^2	0.090
Adjusted R^2	0.007
F	1.08
N	120

p-values in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Table 13: Migration aspirations, CVI & climate change risk perception

CVI	Model 19
Migration aspirations	0.018***
	(0.001)
Financial resources to migrate	-0.034***
	(0.009)
Outside social connections to migrate	-0.019***
	(0.006)
Constant	0.622***
	(0.000)
R^2	0.218
Adjusted R^2	0.198
F	10.768***
N	120

Migration aspirations	Model 20
CVI	4.428***
	(0.001)
Constant	-0.923
	(0.244)
R^2	0.087
Adjusted R^2	0.079
F	11.25***
N	120

p-values in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Migration aspirations	Model 21
Risk of climate-induced events	0.121
	(0.429)
Concerned for climate change	0.089
	(0.114)
Risk for standard of living	-0.147*
	(0.078)
Chances of family survival	0.012
	(0.826)
Constant	1.410*
	(0.064)
R^2	0.054
Adjusted R^2	0.021
F	1.64
N	120

5.5 Robustness check

After performing a bootstrapping robustness check, the different models presenting significant effects were reanalyzed (Appendix J).

5.5.1 Original multiple moderated linear regression

Firstly, the original multiple linear regression regarding climate change risk perception and vulnerability (Model 6) was bootstrapped. The positive significant effect of *risk of climate-induced events* on the *CVI* at $p<0.05$ ($\beta = 0.017$) remains significant. Additionally, the negative significant effect of *education* on the *CVI* at $p<0.05$ ($\beta = -0.004$), the negative significant effect of *income* at $p<0.01$ ($\beta = -0.000$), and the positive significant effect of *village* at $p<0.01$ ($\beta = 0.009$) on *CVI* all persist. Thus, these results are robust. However, after bootstrapping Model 8, which examines the moderating effects of bonding social capital, the negative significant effect of *bonding social capital* on the relationship between *chances of family survival* and *vulnerability* is not observed. Thus, the robustness of this result cannot be confirmed.

5.5.2 Intersectionality

The bootstrapped Model 9 shows similar results to the original Model 9. Again, only the intersection between *age* and *education* shows a negative significant effect on the *CVI* at $p<0.05$ ($\beta = -0.0004$), ensuring the robustness of this statistic. Furthermore, the negative significant effects of *gender* ($\beta = -0.110$) and *income* ($\beta = -7.22\text{e-}06$) on *risk of climate-induced events* at $p<0.05$ and $p<0.1$, respectively, also hold in the bootstrapped Model 11. Moreover, the negative significant effect of *age* ($\beta = -0.011$) on *chances of family survival* is present in the bootstrapped Model 14. Thus, both effects of socio-demographic characteristics on climate change risk perception are robust. Lastly, the positive significant effect of the interaction between *education* and *income* on *concerned for climate change* at $p<0.05$ ($\beta = 0.000$) is also observed in the bootstrapped Model 16, confirming the robustness of this intersectionality effect.

5.5.3 Migration aspirations & capabilities

The bootstrapped Model 19 also presents the same significant effects of *migration aspirations, financial resources to migrate*, and *outside social connections to migrate* on the *CVI* at $p<0.01$ ($\beta = 0.018$; $\beta = -0.034$; $\beta = -0.019$). Moreover, the positive effect of the *CVI* on *migration aspirations* also holds in the bootstrapped Model 20 at $p<0.01$ ($\beta = 4.423$), indicating these relationships are robust. Finally, the effect of *climate change risk perception* on *migration* *aspirations* is also present in the bootstrapped Model 21, where the *risk for standard of living* has a negative significant effect at $p<0.1$ ($\beta = -0.147$). Thus, these effects are also robust.

Table 14 presents all hypotheses drawn from the literature review and indicates which ones are supported. Although some hypotheses may not be supported, different significant relationships have emerged. A detailed analysis of the results will be provided in the 'Discussion' section.

	Model	**Original regression**	**Bootstrapped regression**
Hypothesis	**Supported**		
H1: Climate change risk perception has a decreasing effect on the vulnerability of ENMs.	2 - 6	No	No
H2: Bonding social capital strengthens the negative relationship between climate change risk perception and the vulnerability of ENMs.	7 - 8	No	No
H3a: Gender has an increasing effect on the vulnerability of ENMs.	1	No	No
H3b: Age has an increasing effect on the vulnerability of ENMs.	1	No	No
H3c: Education has a decreasing effect on the vulnerability of ENMs.	1	Yes	Yes
H3d: Income has a decreasing effect on the vulnerability of ENMs..	1	No	No
H3e: Intersectionality influences the vulnerability of ENMs.	9 - 10	Partially	Partially
H4a: Gender has an increasing effect on the climate change risk perception of ENMs.	11 - 14	No	No
H4b: Age has a decreasing effect on the climate change risk perception of ENMs.	11 - 14	Partially	Partially
H4c: Education has an increasing effect on the climate change risk perception of ENMs.	11 - 14	Partially	Partially
H4d: Income has a decreasing effect on the climate change risk perception of ENMs..	11 - 14	Partially	Partially
H4e: Intersectionality influences the climate change risk perception of ENMs.	15 - 18	Partially	Partially
H5a: Migrations aspirations have an increasing effect on the vulnerability of ENMs.	19	Yes	Yes
H5b: Financial resources to migrate have a decreasing effect on the vulnerability of ENMs.	19	Yes	Yes
H5c: Outside social connections to migrate have a decreasing effect on the vulnerability of ENMs.	19	Yes	Yes
H5d: The vulnerability of ENMs has an increasing effect on migration aspirations.	20	Yes	Yes
H5e: The climate change risk perception of ENMs has an increasing effect on migration aspirations.	21	No	No

Table 14: Results from regression analyses & robustness checks

5.6 Geographical Information System (GIS)

To analyze the spatial dimension of this study, a map was created using QGIS (Figure 4). On this map, the villages Tipna, Gonali, and Purbapara are located in the north, Kodomtola is located in the west, and Tayabpur in the southeast. Coordinates from each respondent were collected, and the *CVI* was connected to the corresponding coordinates. As shown on this map, the highest *CVI* scores are found in Tayabpur, which is closest to the coast and other waterbodies. In the northern part of Dumuria Upazila, the lowest *CVI* scores are observed, situated the furthest away from the coast and waterbodies.

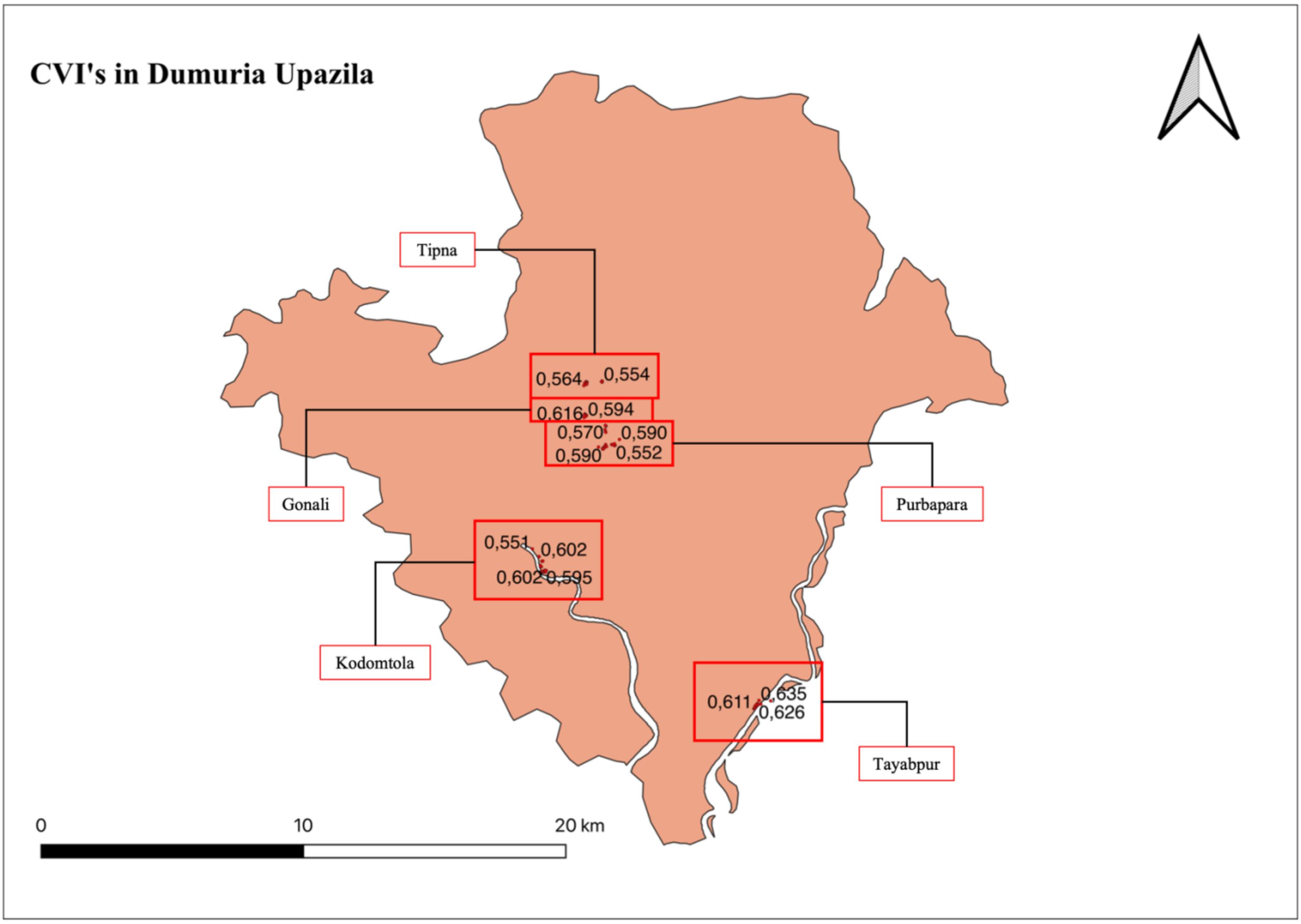

Figure 4: CVI's in Dumuria Upazila

6. Discussion

In this section, an analysis of the results will be conducted. The hypothesized effects between climate change risk perception and the vulnerability of ENMs, the moderating effect of bonding social capital on this relationship, the effects of intersectionality, and the role of migration aspirations and capabilities in this context have been tested.

6.1 Vulnerability in Dumuria Upazila

To fully understand the relationship between climate change risk perception and the vulnerability of ENMs, it is essential to delve deeper into the three dimensions of vulnerability to climate change within Dumuria Upazila. As previously stated, the CVI within the sample ranges from 0.533 to 0.654, with Tayabpur in the southeast being the most vulnerable village (mean = 0.624), and Tipna in the northwest being the least vulnerable village (mean = 0.568). Several trends can be recognized throughout the entire sample.

6.1.1 Exposure

Firstly, when analyzing the degree to which ENMs in Dumuria Upazila are exposed to climate change, the indicator scores are relatively similar. As the study area is only 454,2 km^2 – 0.003% of Bangladesh's land area – factors such as maximum average monthly temperature, and groundwater salinity are consistent (BBS, 2021). However, the specific natural disaster that has the greatest impact on the population varies among the villages. For example, Tipna is less affected by river flooding than Tayabpur and Kodomtola, but more so by cyclones. Despite these differences, the overall exposure is similar due to the close proximity of the villages. The average score on this dimension is 0.691 out of 1, indicating a moderate to high level of exposure to climate change. Increasing temperatures negatively affect farmers' crops and lead to new varieties of insects that disrupt the crop-growing process. The chemicals used to repel these insects no longer work effectively, resulting in many unsuccessful yields. Moreover, higher temperatures have also caused longer dry periods, reducing the depth of rivers, affecting aquaculture. Therefore, fishermen may have difficulties catching fish to sustain their livelihoods, leading them to more extreme poverty.

6.1.2 Sensitivity

The sensitivity to climate change shows more variation among the respondents (SD = 0.060) than exposure, as it is influenced by community and individual level factors. Trends observed are: 95% of the respondents live below the international poverty line of $2.15 per capita per day, with the remaining respondents living below the international moderate poverty line of $3.65 per capita per day. Moreover, 47% of the respondents' households depend on selling fish, indicating high aquacultural dependency. Keeping livestock is often used as a livelihood strategy to ensure future income, but is considered costly due to the high costs of feeding animals. Overall, the people in Dumuria Upazila are highly dependent on their agricultural and aquacultural productivity, impacting their above average sensitivity to climate change. Differences in sensitivity among the villages include that Tayabpur is most densely populated, contributing to its overall high vulnerability. Additionally, this village is also located the furthest away from the upazila HQ, Dumuria, affecting their ability to sell fish in different markets.

6.1.3 Adaptive capacity

Lastly, adaptive capacity is primarily influenced by individual and household factors, but some trends can still be identified: most respondents possess a mobile phone, although often not a smartphone, which they use to keep in contact with their family and friends. However, 49% of the respondents do not use the internet on their phone, as this is often only possible when using a smartphone. All respondents have access to electricity for lighting and charging electronic devices, as this was part government plans to provide electricity to all in Bangladesh (Daily Star, 2022). Regarding other basic facilities, almost none of the respondents have a 'pucca' or cement-structured sanitation facility, although 33% live in a pucca or semi-pucca household. Poor hygiene can lead to higher chances of diseases, for example through the spreading of bacteria from contaminated food when hands are not washed properly before preparation (Nizame et al., 2016). This greatly affects the respondents' vulnerability. Despite a high literacy rate, easy access to primary and secondary schools varies among the villages. Finding a primary school nearby is relatively easy, but accessing a secondary school requires more effort. Many respondents have only attended primary school, or have not attended education at all. Another issue raised during conversations is the lack of cyclone centers in Dumuria Upazila. Despite frequent cyclones, centers to protect the people are often very small or nonexistent. Poor road infrastructure and the cost of mobility make reaching distant cyclone centers challenging.

Often, school buildings are used as shelters. Altogether, these factors greatly impact the adaptive capacity of the people in Dumuria Upazila, impacting their degree of vulnerability.

Overall, vulnerability to climate change of ENMs in Dumuria Upazila is above average, with respondents from Tayabpur scoring the highest and respondents from Tipna scoring the lowest on the CVI. This finding aligns with Ali & Erenstein (2017), who argue that those in more rural areas are commonly more susceptible to climate change, increasing their vulnerability. This is also evident in the study area map constructed using QGIS, where the highest scoring village, Tayabpur, is situated on the riverbanks of the Rupsha River, greatly impacting their livelihoods. This village is affected by the river drying up during the dry season, negatively impacting their ability to catch fish to eat and sell, as well as by river floods during rainy season, damaging their houses and increasing their overall vulnerability to climate change.

6.2 The effect of climate change risk perception on the vulnerability of ENMs

To understand how risks of climate change are perceived and how these perceptions may impact ENMs' livelihood and disaster response strategies, several dimensions of risk perception are analyzed. This sample suggests that there is no real effect between concerns for climate change, the perceived risk of climate change for the standard of living, the perceived chances of family survival in the context of climate change, and the vulnerability of ENMs. However, a significant positive relationship has been detected between the perceived risk of climate-induced events and the vulnerability of ENMs. Therefore, this relationship will be investigated more deeply in the next section.

6.2.1 Perceived risk of climate-induced events

A positive significant effect between the perceived risk of climate-induced events and the vulnerability of ENMs is observed across all original regression models, as well as after performing a robustness check. This finding contradicts Bradley et al. (2020), who established a positive relationship between the perceived severity of risks and a person's belief that the outcome of their risk response will be positive. Nevertheless, it aligns with the findings of Khan et al. (2020), implying that greater shocks stemming from climate change, such as perceiving climate-induced effects as severe, may increase the vulnerability of disadvantaged groups. Thus, when the risks of natural disasters, such as rising sea levels and cyclones, are perceived as severe, the vulnerability of ENMs increases.

Next, the question arises: what exactly causes this increase? Although adaptive strategies often arises when climate change is well-perceived, the overall presence of climate change risks ultimately increases vulnerability (Adger et al., 2020; Smit & Skinner, 2002). Respondents from Tipna (mean = 4.400) and Tayabpur (mean = 4.275) score the highest on perceived risk of climate-induced events. These villages are very densely populated, implying that a climate change hazard would impact a larger group of ENMs. Additionally, both villages are highly dependent on aquaculture, which is affected by many climate-induced events, such as increased temperatures, longer dry periods, and river flooding.

When comparing Tayabpur to Kodomtola, both villages are situated close to a river. However, the population of Kodomtola is less dependent on aquaculture, as many respondents also own livestock, which is much less common in Tayabpur. Overall, this implies that both Tipna and Tayabpur are highly exposed to climate change, which is the dimension of vulnerability that, on average, has the highest weight in the CVI within this sample.

Although prior studies have shown that higher risk perception can decrease vulnerability to climate change through effective risk response and adaptive strategies, this sample presents the opposite (Bradley et al., 2020; Smit & Skinner, 2002). Nevertheless, given that the beta coefficient is very small ($\beta = 0.017$), the risk of climate-induced events is not the only determining factor of vulnerability, which will be discussed in the next sections.

6.3 The role of bonding social capital

To respond to calls for research into the social factors influencing risk perceptions and behavior of ENMs, the effect of bonding social capital on the relationship between their climate change risk perception and vulnerability was tested (Mallick, 2023; Van der Linden, 2015). Unfortunately, most interactions between risk perception and vulnerability yielded no significant results, except for the relationship between the chances of family survival and vulnerability. A negative significant effect was detected in this context, implying that higher bonding social capital, through strong ties within the family, with neighbors, and within the community, weakens the relationship between the perceived chances of family survival and vulnerability.

In the original regression (Model 6), the relationship between the chances of family survival and vulnerability was positive but insignificant. This suggests that without bonding social capital, higher perceived chances of family survival in a climate disaster might increase the vulnerability of ENMs, potentially due to a lack of implemented adaptive strategies.

However, when bonding social capital is high, this effect is weakened. This finding aligns with Gifford & Nilsson (2014), who noted that close communities can influence each other's attitudes and behaviors towards climate change and provide mutual support during crises (Islam et al., 2020).

Nevertheless, this single significant interaction effect did not hold after performing a robustness check. Thus, while some conclusions can be drawn, the effect of bonding social capital on the relationship between risk perception and vulnerability is not conclusively justified by this sample.

6.4 Intersectionality

The effects of different socio-demographic statistics on the perception of climate change risk and the vulnerability of ENMs in this sample were tested. Before diving deeper into the effects of intersectionality on these two concepts, the separate effects of the different characteristics are explained.

6.4.1 Gender

Although no real effects were found between gender and vulnerability to climate change, a negative significant effect was observed on the risk of climate-induced events. This implies that women tend to perceive the risk of climate-induced events as lower than men, which contradicts prior studies emphasizing the opposite (Van Eck et al., 2020; Van der Linden, 2015). In the context of Dumuria Upazila in Bangladesh, men often work outside of the house, frequently exposed to the effects of climate change, such as increasing temperatures and reduced agricultural productivity, while women tend to stay at home. This might cause women to perceive the effects of climate change as less severe than men. However, out of the four subcategories used to measure risk perception, only one showed significant gender effects.

6.4.2 Age

Despite not detecting a significant relationship between age and the vulnerability of ENMs, a negative significant relationship was found between age and perceived chances of family survival. Older respondents perceived their family's chances of surviving a climate disaster as lower than younger respondents. Bradley et al. (2020) found that older people often have lower response efficacy, meaning that they believe their actions to mitigate the adverse effects of environmental risks are less effective. This finding explains why older people in this sample tend to perceive their family's survival chances as low.

6.3.3 Education

Contrasting previous characteristics, no real relationship was detected between a respondent's level of education and their climate change risk perception. Nevertheless, a negative significant effect was found between education and the vulnerability of ENMs, implying that a higher level of education lowers their vulnerability to climate change. Education can increase adaptive capacity through access to resources and information, which decreases vulnerability and explains the detected relationship (Muttarak & Lutz, 2014).

6.3.4 Income

Income does not present any significant effects on the respondents' perception of climate change risk, but a significant negative effect was found between income and vulnerability. This means that a higher household income implies a lower degree of vulnerability of ENMs. This finding corresponds with previous studies emphasizing the decreasing effect of income, as higher-income individuals have greater opportunities to access resources to adapt to the adverse effects of climate change, thereby decreasing their vulnerability (Cox & Kim, 2018; Muttarak & Lutz, 2014). Still, the beta coefficient is extremely small ($\beta = -0.000$), implying an almost negligible effect of income, which can be explained by the very small variations in income within this sample.

6.3.5 Interaction effects of intersectionality on climate change risk perception and vulnerability

The intersection between different socio-demographic characteristics has been tested on both climate change risk perception and vulnerability of ENMs, revealing minimal effects overall. However, some interaction terms between characteristics show significant effects. The interaction between education and income positively affects the degree of concern for climate change, and this effect remains significant after robustness checks. This indicates that individuals with higher education and income levels are more concerned about the effects of climate change than less educated individuals earning lower salaries. As previously explained, higher income provides greater access to resources, while higher education improves access to information (Gilbert & Lachlan, 2023; Muttarak & Lutz, 2014; Van Eck et al., 2020). The interaction between these socio-demographic characteristics enhances knowledge of the adverse effects of climate change, which may increase concerns about it.

Additionally, the interaction between age and education presents a significant negative effect on the vulnerability of ENMs, which also holds after robustness checks. This implies that being older and more educated decreases vulnerability to climate change. This finding aligns with earlier studies suggesting that attaining a certain level of education provides greater opportunities to access resources and information to reduce vulnerability (Muttarak & Lutz, 2014). Although prior literature has often emphasized the higher vulnerability of older people to climate change due to health conditions and lower mobility, higher education levels often come with age, explaining the interaction between education and age (Adams et al., 2021; Mallick, 2023).

6.4 Non-migration decisions

Lastly, as the respondents within the sample remain in their place of residence despite the risk of environmental hazards, analyzing the relationship between vulnerability and migration aspirations and capabilities can provide further insights into the livelihoods of ENMs. This analysis is useful for policymakers and contributes to a more comprehensive understanding of the drivers that influence non-migration decisions (Naser et al., 2023; Mallick, 2023). As explained earlier, the ENMs within this sample can mostly be referred to as 'trapped' (72%), as they aspire to migrate, but lack the financial or social resources to do so. Additionally, this sample includes cases of 'acquiescent immobility', where individuals lack both migration aspirations and the resources to migrate (Schewel, 2019). A common reason for staying put in their village is that, compared to cities, villages provide cooler places with trees and ponds, as well as more space for each individual, particularly as temperatures increase.

6.4.1 Migration aspirations, capabilities, and vulnerability

When analyzing the effects of vulnerability on migration aspirations and vice versa, a positive significant effect of vulnerability on migration aspirations is detected. This means that higher vulnerability increases the aspiration to migrate to a different location, aligning with McLeman & Gemenne (2018), who state that adverse environmental changes drive the aspiration to migrate to less affected areas. Moreover, a positive significant relationship is also observed when assessing the reverse relationship, indicating that the more a respondent wants to move to a different location, the higher the vulnerability to climate change. This findings corresponds with Gilodi et al. (2022), and can potentially be explained by the lack of effort put into adaptive strategies due to the desire to migrate.

Furthermore, having financial resources and outside social connections decrease the vulnerability of ENMs, which aligns with the positive effect of a higher income on vulnerability. This also corresponds with Van Praag (2021), who states that a lack of bridging social capital, such as through remittances, decreases a person's capability to migrate (Cox & Kim, 2018; Muttarak & Lutz, 2014).

6.4.2 Climate change risk perception and migration aspirations

The sample presents that the higher the perceived risk for the effects of climate change on the standard of living of the respondents, the lower the migration aspirations. This corresponds with Mallick (2023), stating that those who perceive the risks of climate change well, often accept that they will have to take action to protect their livelihoods, decreasing their wishes to migrate.

6.4.3 Voluntary and trapped ENMs

In Dumuria Upazila, trapped ENMs are shown to be more vulnerable to climate change on average than voluntary ENMs, most likely due to their lack of financial or social resources to migrate. While voluntary ENMs choose to stay, trapped ENMs lack this decision-making capability. Moreover, bonding social capital is slightly higher for voluntary ENMs, likely linked to their lack of migration aspirations, as their community's cohesion is high. For trapped ENMs, higher vulnerability and lack of resources may contribute to lower bonding social capital, as they struggle to support their community financially, and participating in communal activities may not be their priority, as they already have to sustain their livelihoods and manage their own vulnerability.

7. Conclusion

This study analyzed the complex interplay between climate change risk perception, vulnerability to climate change, bonding social capital, intersectionality, and migration aspirations and capabilities among ENMs in Dumuria Upazila. The research questions addressed were: 'How does climate change risk perception affect the vulnerability of environmental non-migrants in hazard-prone coastal areas in Bangladesh?', 'How does bonding social capital moderate this relationship?' and 'How does intersectionality affect the perception of climate change risk and the vulnerability of environmental non-migrants?'. The findings provide both theoretical and practical implications, highlighting the importance of localized and context-specific policy interventions to reduce the unique vulnerabilities of ENMs. Moreover, several limitations to the study are presented, and suggestions for future research are offered.

7.1 Theoretical implications

Throughout this research, several gaps have been addressed regarding climate change risk perception and the vulnerability of ENMs. Previous research has often overlooked those who remain in their place of residence although at risk of climate change, unable or unwilling to use migration as an adaptive strategy. By analyzing the unique vulnerabilities and risk perceptions of those most affected by climate change, specifically ENMs in Dumuria Upazila, this study contributes to literature on non-migration and enhances the understanding of how climate change impacts ENMs, important for future policymaking. Besides, it responds to calls for more localized vulnerability indices (Ahsan & Warner, 2023).

The results challenge prior studies suggesting that higher risk perception decreases vulnerability through adaptive strategies as a risk response (Bradley et al., 2020, Smit & Skinner, 2002). Instead, this study provides evidence that higher perceived risk of climate-induced events increases the vulnerability of ENMs. This highlights the importance of considering context when studying vulnerability and risk perceptions. By employing a geospatial mixed methods research design, this research enriches development studies, by offering a nuanced understanding of this unique context through multiple methodological perspectives (Harris, 2022).

Although previous research has emphasized the potential role of bonding social capital in enhancing adaptive capacity of a community, by providing mutual support during crises, this study does not conclusively support this effect (Gifford & Nilsson, 2014). Additionally, the significant effects of intersectionality through different socio-demographic characteristics presents the need to consider the compounded effects of social determinants when assessing risk perceptions and vulnerability. This finding underscores the necessity for less simplistic and more comprehensive studies on environmental non-migration.

Lastly, this study presents the effects of migration aspirations and capabilities on both risk perceptions as well as vulnerability, elucidating why ENMs decide to stay put. This again adds to literature on environmental non-migration, and generates practical implications to establish and support livelihood-resilient practices (World Bank, 2024).

7.2 Practical implications

The findings to this study result in various practical implications, emphasizing the need for developing policy interventions and climate changes adaptation strategies to address the specific vulnerabilities and needs of ENMs. First of all, the unique circumstances of ENMs in Dumuria Upazila, who often aspire to migrate but are financially or socially unable to do so, highlight the importance of considering the prominent impact of the local climatic conditions, such as high temperatures during dry season and floods during rainy season. Additionally, livelihood conditions, such as poverty, income sources, and population density, as well as adaptive capacities, such as the availability of cyclone centers, proper sanitation facilities, and schooling possibilities, should be considered when developing context-specific policies to combat the adverse effects of climate change on this area. Long-term development initiatives should be established to improve the overall socio-economic circumstances in which ENMs in Dumuria Upazila reside.

Secondly, the positive relationship between perceived risk of climate-induced events and the vulnerability of ENMs suggests that simply increasing awareness on the risks of these events is not enough to enhance community resilience. Effective interventions should include informing ENM communities on the projected risks of specific events and providing opportunities to mitigate and adapt to these risks. This could involve investing in more pucca housing, improving local infrastructures, and ensuring access to facilities and services during a climate-induced events, which will enhance overall community resilience.

Thirdly, as this study highlights the effects of socio-demographic characteristics and their intersection on the vulnerability to climate change, it is essential to consider these when establishing climate change policies for ENMs. Those with lower education levels, lower income levels, as well as older and less educated ENMs, require more support to decrease their vulnerability. This can be ensured through tailored and equitable interventions. Overall, the emphasis should be on inclusive climate change adaptation policies, by building on local knowledge and including vulnerable groups into decision-making processes, while also leveraging the role of bonding social capital in enhancing livelihood resilience. Moreover, when establishing internal migration policies, considering both the migration aspirations and capabilities of ENMs is important. Policies should support those who wish to remain in their communities but also those who wish to migrate, by alleviating the burdens of vulnerability that might hinder mobility and focus on providing necessary resources to enhance livelihood resilience.

7.3 Limitations

This study presents several methodological limitations that may have affected the outcomes. Firstly, the cross-sectional research design limits the ability to draw conclusions on how climate change risk perceptions impact the vulnerability of ENMs over time. Additionally, climate change risk perceptions may vary throughout the year due to the occurrence of different climate-induced events, while data for this study was only collected in March 2024. Although the sample size threshold for multiple linear regression analyses was met, a larger sample size would enhance the generalizability and robustness of the results (Green, 1991). Moreover, as this study focuses on both voluntary and trapped ENMs, a more equal representation of these two groups could enhance generalizability across other ENM communities. Since the data was collected in Bangla, translation mistakes or researcher bias may have occurred, despite all questions being checked prior to conducting the surveys together with the research assistant.

When analyzing the operationalization of each variable, some limitations are presented. Firstly, although most variables are measured at the individual level, such as gender, age, and risk perception, some indicators of vulnerability are measured at the community level, such as maximum temperatures and soil salinity. This may affect the generalizability of the study and consistency in the interpretation of the data. Furthermore, as the indicators for vulnerability are specified to match the local context of Dumuria Upazila, this indexing may not be applicable to all other areas where ENMs reside. Lastly, although this study covers many different aspects and drivers of ENM livelihoods, there may still be additional factors influencing climate change risk perception that were not included in this study.

7.4 Suggestions for future research

As this study has its limitations, these also provide new areas for future research. Firstly, future research could use panel data to analyze the effects of risk perceptions on vulnerability over a longer period of time. Secondly, employing a qualitative research design to understand the narratives behind perceptions of climate change risk, could enhance the understanding of how these perceptions arise. Moreover, to increase validity and generalizability of the results, a larger sample size could be deployed, collecting data from additional villages within Dumuria Upazila, or even expanding the geographical scope to other vulnerable coastal areas in Bangladesh, such as Koyra Upazila.

When expanding this study, the CVI should be revised, as some indicators may be more relevant when assessing a different vulnerable area. Given the significant effects of socio-demographic characteristics and their intersection on both risk perception and vulnerability, analyzing these effects using different characteristics could yield even more insights into the drivers of the main concepts. Lastly, future research could also explore the significant effects of outside social connections, or bridging social capital, and its potential to moderate the relationship between climate change risk perception and the vulnerability of ENMs.

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Appendices

Appendix A: Survey questions

Survey IDS Master's Thesis - Climate Change Risk Perception in Dumuria Upazila

Record your current location

breedtegraad (x.y °)

lengtegraad (x.y °)

hoogte (m)

nauwkeurigheid (m)

What is the name of the union?

- ◯ Shorafpur
- ◯ Shovna
- ◯ Kharnia

What is the name of the village?

What is the gender of the respondent?

- ◯ Male
- ◯ Female
- ◯ Other

What is the age of the respondent?

What is your level of education?

- ◯ None
- ◯ Primary school
- ◯ Secondary school
- ◯ Post-secondary non-tertiary school
- ◯ Bachelor's degree or equivalent
- ◯ Master's degree or equivalent
- ◯ Doctoral or equivalent
- ◯ Higher

What is your household's main source of income?

- ◯ Sale of crops
- ◯ Sale of livestock & products
- ◯ Sale of fishes & fisheries
- ◯ Shopkeeper (business)
- ◯ Formal work
- ◯ Other

What is your average monthly household expenditure (in BDT)?

____

Do you currently have any loans?

- ◯ Yes
- ◯ No

What is your average monthly household income (in BDT)?

____

Do you believe in climate change?

- ◯ Yes
- ◯ No

How concerned are you about climate change?

- ◯ Not concerned
- ◯ Slightly concerned
- ◯ Moderately concerned
- ◯ Concerned
- ◯ Very concerned

What is the biggest environmental risk in this village?

- ◯ Coastal flooding
- ◯ Cyclones
- ◯ Both
- ◯ None

I think that climate change will have a negative effect on the agricultural productivity of the land in this village

- ◯ Strongly disagree
- ◯ Disagree
- ◯ Undecided
- ◯ Agree
- ◯ Strongly agree

I think that river level rises will have a negative effect on this village

- ◯ Strongly disagree
- ◯ Disagree
- ◯ Undecided
- ◯ Agree
- ◯ Strongly agree

I think that more heavy rainfall will have a negative effect on this village

- ◯ Strongly disagree
- ◯ Disagree
- ◯ Undecided
- ◯ Agree
- ◯ Strongly agree

I think that an increased number of cyclones will have a negative effect on this village

- ◯ Strongly disagree
- ◯ Disagree
- ◯ Undecided
- ◯ Agree
- ◯ Strongly agree

I think that increased surface temperatures will have a neggative effect on this village

- Strongly disagree
- Disagree
- Undecided
- Agree
- Strongly agree

I think that climate change will lead to more pests and diseases in this village

- Strongly disagree
- Disagree
- Undecided
- Agree
- Strongly agree

I think that my standard of living will decrease due to climate change

- Strongly disagree
- Disagree
- Undecided
- Agree
- Strongly agree

I think that my family can survive extreme weather events with good planning

- Strongly disagree
- Disagree
- Undecided
- Agree
- Strongly agree

How many close friends do you have? (estimate)

____

How well do people in your village help each other out when in need?

- Never
- Rarely
- Sometimes
- Very often
- Always

How much do you trust the people in your village?

- Not at all
- Slightly
- Moderately
- Very much
- Totally

Would you contribute to a project in your village when it does not benefit you?

- Yes
- No

Does your household participate in communal activities in the village?

- Yes
- No

If you suddenly needed a small amount of money, would your neighbour be willing to give that to you?

- Yes
- No

Do you ever ask your relatives or friends for advice or emotional support?

- Never
- Rarely
- Sometimes
- Very often
- Always

Has the maximum temperature decreased, increased or remained the same in this village during the last five years?

- Decreased
- Increased
- Remained the same

Has the rainfall decreased, increased or remained the same in this village during the last five years?

- Decreased
- Increased
- Remained the same

Has the number of cyclones decreased, increased or remained the same in this village during the last five years?

- Decreased
- Increased
- Remained the same

Has the number of floods decreased, increased or remained the same in this village during the last five years?

- ◯ Decreased
- ◯ Increased
- ◯ Remained the same

Has the salinity of the drinking water decreased, increased or remained the same in this village during the last five years?

- ◯ Decreased
- ◯ Increased
- ◯ Remained the same

Has the length of dry periods decreased, increased or remained the same in this village during the last five years?

- ◯ Decreased
- ◯ Increased
- ◯ Remained the same

What is the average duration of a dry period in months per year in this village?

____

Does your household own any agricultural land?

- ◯ Yes
- ◯ No

How many livestock does your household own? (cows & goats)

____

Is it easy for you to travel to the Upazila HQ (Dumuria)?

- ◯ Yes
- ◯ No

What vehicle do you use to travel to the Upazila HQ (Dumuria)?

- ◯ Car
- ◯ Motorcycle
- ◯ Easy bike
- ◯ Rickshaw
- ◯ Van
- ◯ Bicycle
- ◯ Other

How many people live in your household?

____

How many people in your household are able to write in Bengali? (are literate)

____

Do you live in a Pucca house made of cement/permanent structure, or in a Kutcha house of a mud structure?

- ◯ Pucca (cement)
- ◯ Kutcha (mud)
- ◯ Semi Pucca

Do you have a good sanitation facility within your house?

- ◯ Yes
- ◯ No

What is the main source of energy fuel in your household?

- ◯ Electricity
- ◯ Natural gas
- ◯ Liquified petroleum gas
- ◯ Coal / wood
- ◯ Petrol / kerosine

What drinking water source do you have in your household?

- ◯ Tap water
- ◯ Shallow tubewell water
- ◯ Deep tubewell water
- ◯ Bottled water
- ◯ Pond-sand filter / rainwater
- ◯ Natural well

Do you use a mobile phone?

- ◯ Yes
- ◯ No

Do you use internet?

- ◯ Yes
- ◯ No

Is there a cyclone/refugee shelter in your village?

- ◯ Yes
- ◯ No

Do you aspire to move from this village?

- ◯ Yes
- ◯ No

Do you have the financial resources to move from this village?

- ◯ Yes
- ◯ No

Do you know anyone outside of your village that could help you move?

- ◯ Yes
- ◯ No

Appendix B: Informed consent form

INFORMED CONSENT FORM

Agreement to participate in MSc. thesis research project

Title: Climate change risk perception and vulnerability of voluntary environmental non-migrants: The effect of bonding social capital in rural Bangladesh

Thank you for taking the time to consider my MSc. thesis research project. I am at your disposal for any questions you might have.

Purpose of the Study
The purpose of this study is to gather data about the effect of climate change risk perception on the vulnerability of environmental non-migrants in Dumuria Upazila, and about how bonding social capital may influence this relationship.

Procedures
As a participant in this study, you will be asked to answer several survey questions. The main use of the information you provide will help me to analyze the effect of climate change risk perception on the vulnerability of environmental non-migrants in Dumuria Upazila, and how bonding social capital may influence this relationship, by using quantitative analysis. The study will take approximately 20-30 minutes to complete.

Risks, discomforts and Benefits
There are no known risks or discomforts associated with participating in this study. The benefits of participating in this study include the potential for contributing to the understanding of the vulnerability of environmental non-migrants in Dumuria Upazila and how climate change risk perception and bonding social capital may impact this.

Confidentiality
Your participation in this study will be kept strictly confidential. Your name will not be associated with any data collected, and any data collected will be kept confidential.

Participation and Withdrawal
Your participation in this study is completely voluntary. You may choose not to participate or you may withdraw from the study at any time without penalty.

Contact Information
If you have any questions or concerns about the research privacy, the treatment of research participants or this study project, please contact Sietske de Veld at or s.l.develd@students.uu.nl or +31 681192129. If you have any complaints regarding the research or the researcher, you may contact the supervisor Dr. Bishawjit Mallick at b.mallick@uu.nl.

I can confirm that (please tick box):

- ☐ I have read and understand the information sheet and consent form of this research project.
- ☐ I have had the opportunity to discuss this study. I am satisfied with the answers I have been given.
- ☐ I agree that my participation in this research project is voluntary and that I have the right to withdraw from the study until the moment that the study has been published, and to decline to answer any individual questions in the study without needing to say why.
- ☐ I understand I will not be paid for my participation.
- ☐ I understand I can ask questions at any point during, before or after the activity about any aspect of the research.
- ☐ I understand that I can request any texts with identifiable features to be blurred, made non-identifiable or removed from the research.
- ☐ I understand that the data collected for this study will be kept confidentially either in a locked facility or as a password-protected encrypted file on a password-protected computer of the researcher, and that audio files or transcripts will be removed after the completion of the research.
- ☐ I understand that the information collected for this study will be used only for research purposes only, such as a MSc thesis, articles, book chapters, published and unpublished work and presentations.
- ☐ I consent to my interview being audio-recorded, and understand I have the right to ask for the audio-recorder to be turned off at any time.
- ☐ I understand that my name will not be used on any documents, presentations or other output of the research.

"I agree to participate in this individual research project and acknowledge receipt of a copy of this consent form and the research project information sheet."

Signature of participant: ____________________________ Date: ______________

"I agree to abide by the conditions set out in the information sheet and I ensure to minimalize harm done to any participant during this research."

Signature of researcher: _____________________________ Date: ______________

Please fill in the following information. It will only be used in case you want to be sent a copy of interview notes and/or transcripts.

Address: ____

Email: ____

Appendix C: Employment & data use agreement

EMPLOYMENT & DATA USE AGREEMENT

Thesis title: Climate change risk perception and vulnerability of voluntary environmental non-migrants: The effect of bonding social capital in rural Bangladesh

Agreement for **Mr. Ashraful Islam**, MSS Economics student at Khulna University, Bangladesh, to be a Research Assistant in **Ms. Sietske de Veld**'s, MSc. International Development Studies student at Utrecht University, the Netherlands, master's thesis research project.

Purpose of the study
The purpose of this study is to gather data through household surveys about the effect of climate change risk perception on the vulnerability of environmental non-migrants in Dumuria Upazila, and about how bonding social capital may influence this relationship.

Employment agreement
Tasks

- Translate survey questions from English to Bengali.
- Assist in conducting household surveys (at least 100 surveys) together with Sietske de Veld, and provide the Researcher with answers given by the respondents.
- Use KoboCollect to collect data gathered from conducting household surveys.

Salary

- 1500 BDT per day.
- Travel & food expenses during the field work will be covered by the researcher.

Duration of the study
Approximately 15-18 days of field work (more if necessary). Starting on Wednesday 13 March 2024, as a pilot day, ending on (maximum – preferably on 31 March 2024) Friday 5 April 2024. Every Tuesday (19 March, 26 March, 2 April 2024), will be a day off.

Data use agreement
All data collected during these household surveys, including the answers given by respondents as well as survey questions, are intellectual property of the Researcher (Ms. Sietske de Veld) and therefore of Utrecht University.

The data collected should be protected and may not be shared with any other people other than Ms. Sietske de Veld and Mr. Ashraful Islam. The collected data may not be distributed among any other person of Khulna University other than Mr. Ashraful Islam. Upon completion of this study, the Research Assistant will delete all data associated with this study.

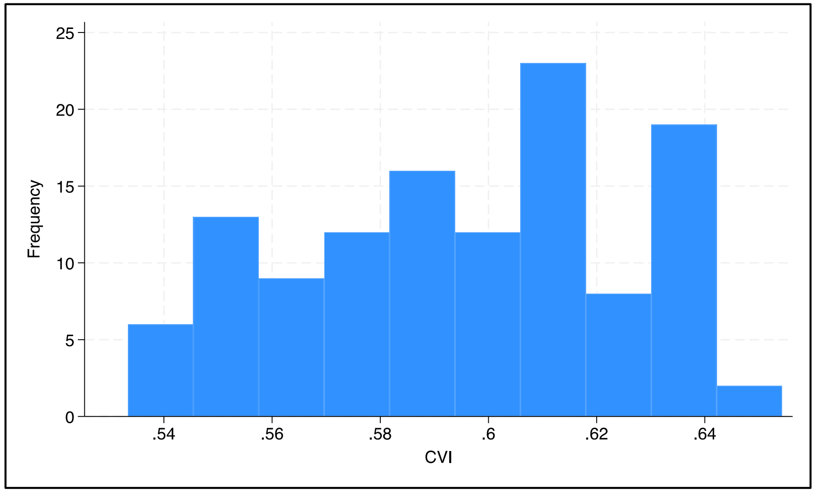
"I agree to have read this agreement and confirm the employment terms and the confidentiality of the data collected in this study."

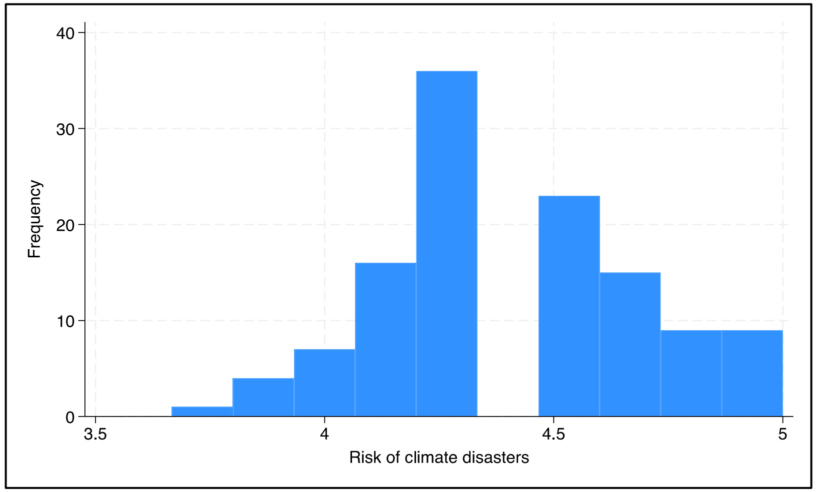
Signature of Research Assistant:
Mr. Ashraful Islam: ____________
Date: 11-03-2024

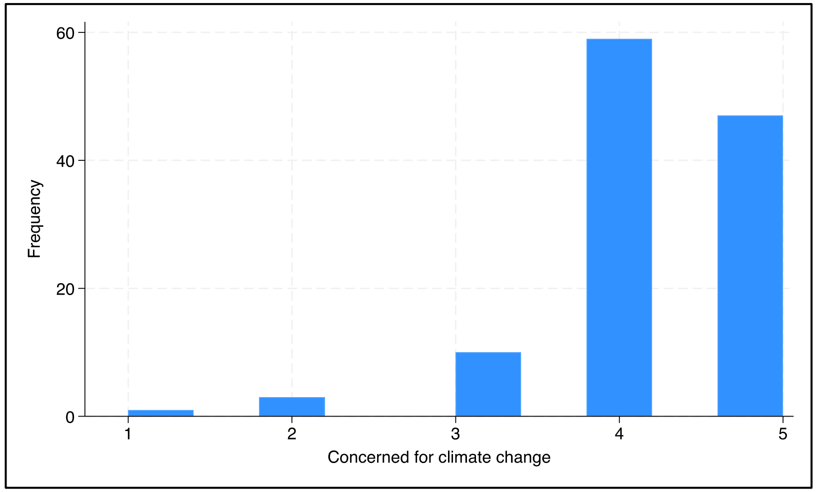
Signature of Researcher:
Ms. Sietske de Veld: ____________
Date: 11-03-2024

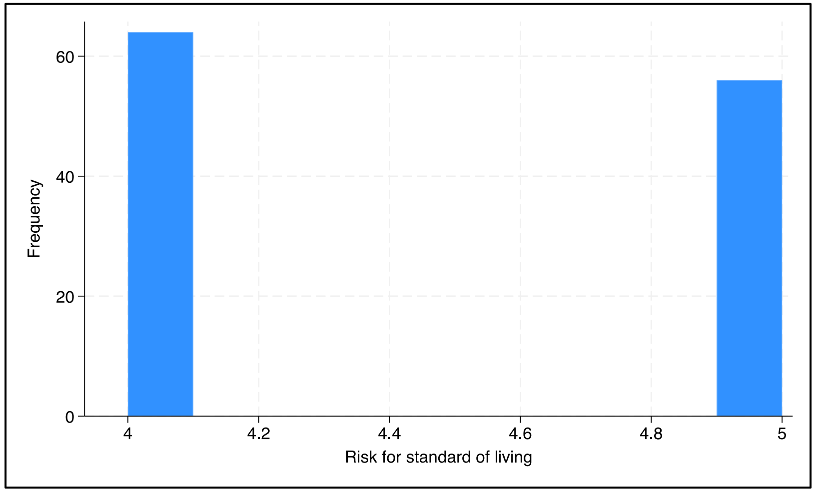
Utrecht University

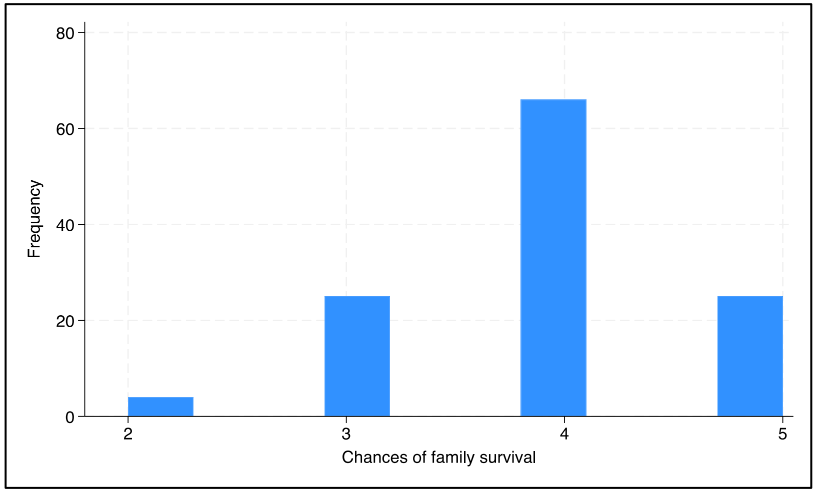
Appendix D: Histograms for outliers







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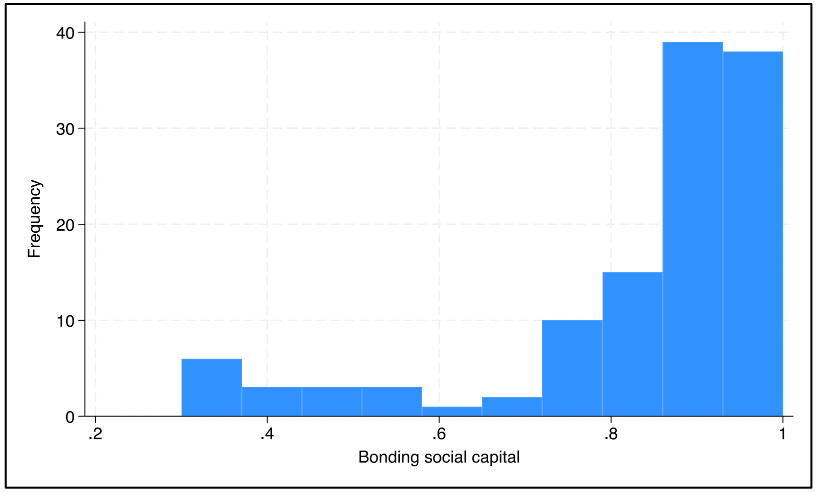
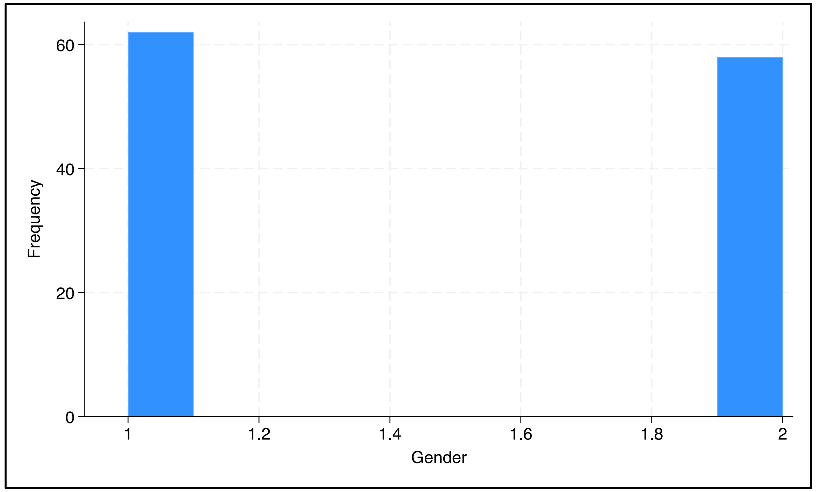
60
40
20
0
2
3
4
5
Chances of family survival


Frequency
40
30
20
10
0
.2
.4
.6
.8
1
Bonding social capital


Frequency
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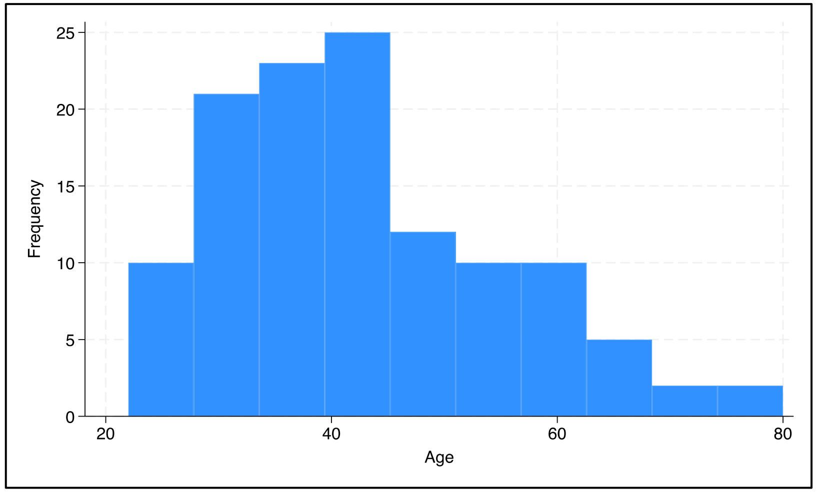
20
0
1
1.2
1.4
1.6
1.8
2
Gender


Frequency
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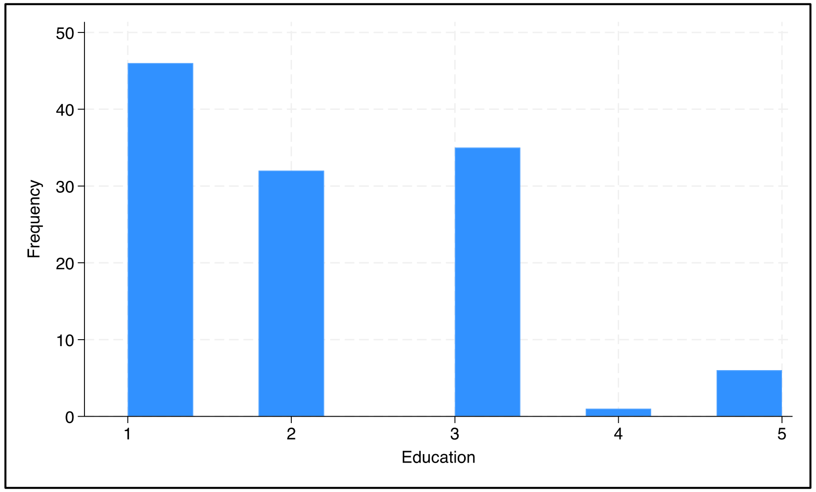
20
15
10
5
0
20
40
60
80
Age


Frequency
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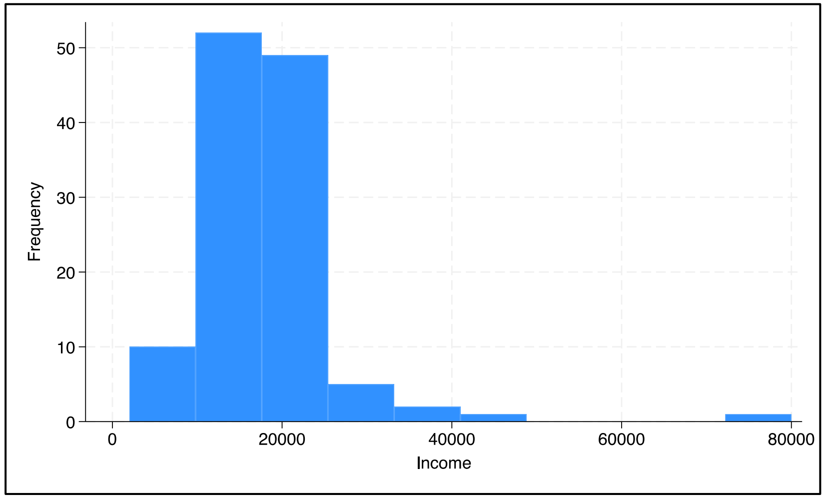
40
30
20
10
0
1
2
3
4
5
Education


Frequency
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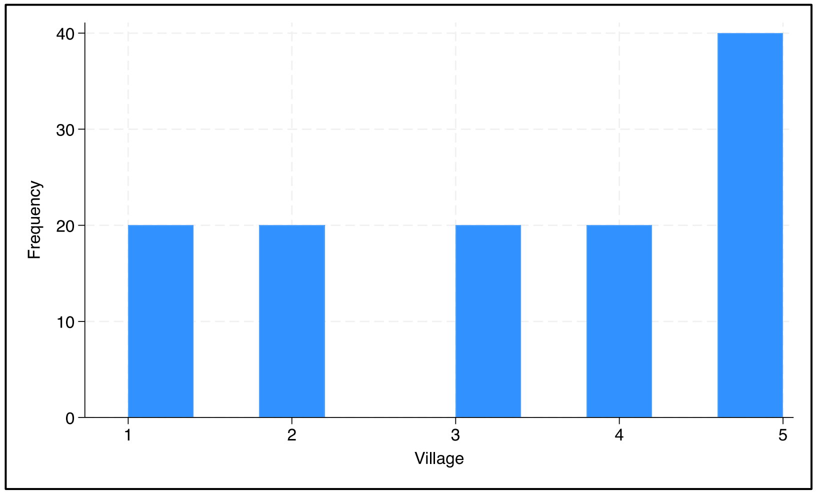
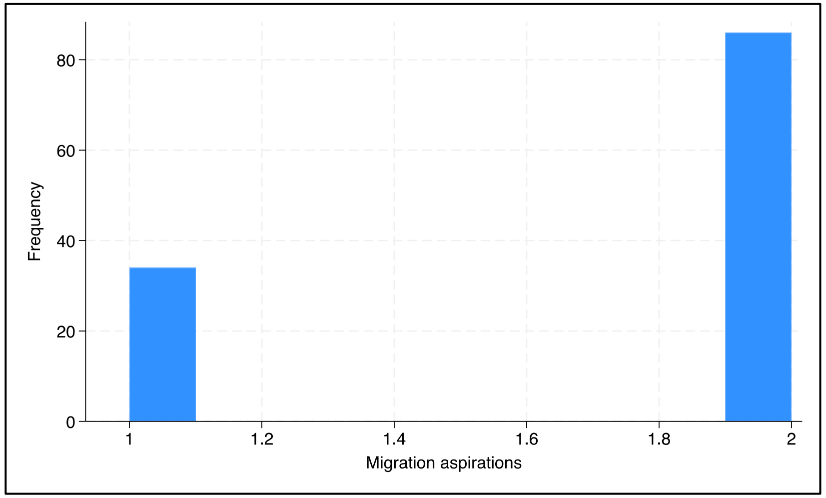
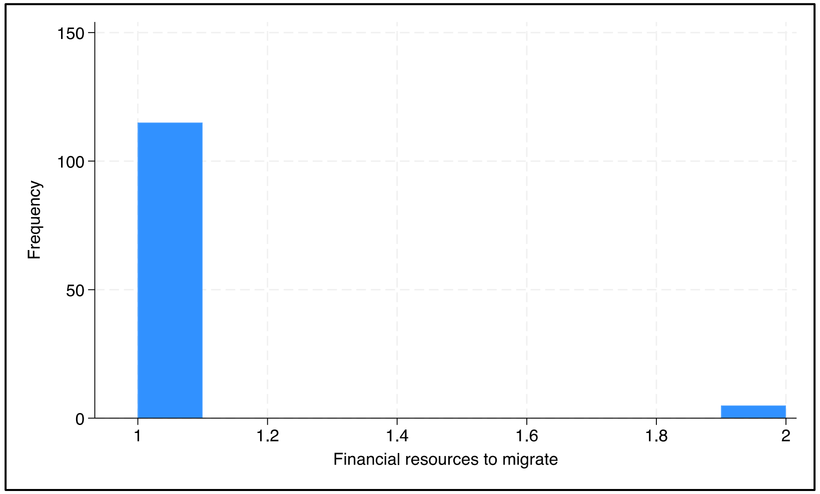
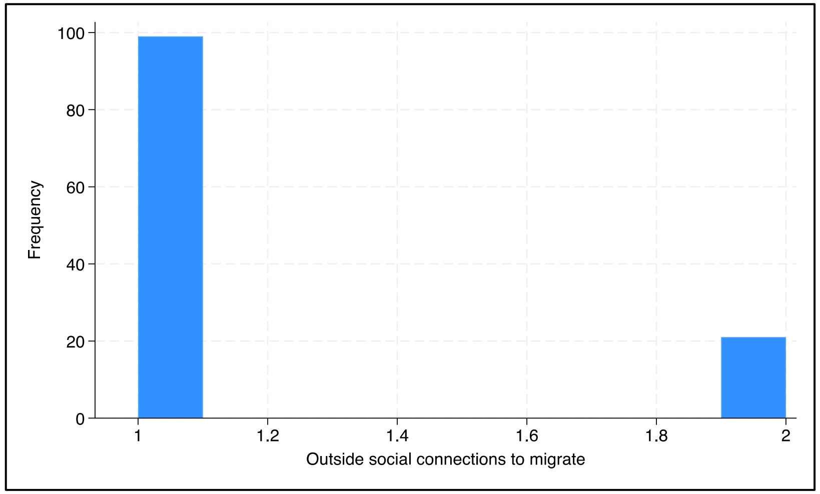
40
30
20
10
0
0
20000
40000
60000
80000
Income


Frequency
40
30
20
10
0
1
2
3
4
5
Village


Frequency
80
60
40
20
0
1
1.2
1.4
1.6
1.8
2
Migration aspirations

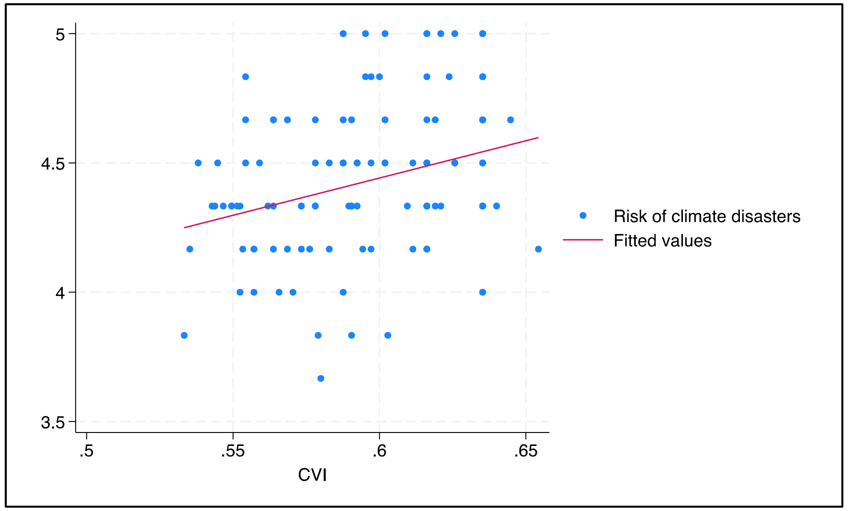

150
100
50
0
Frequency
1
1.2
1.4
1.6
1.8
2
Financial resources to migrate

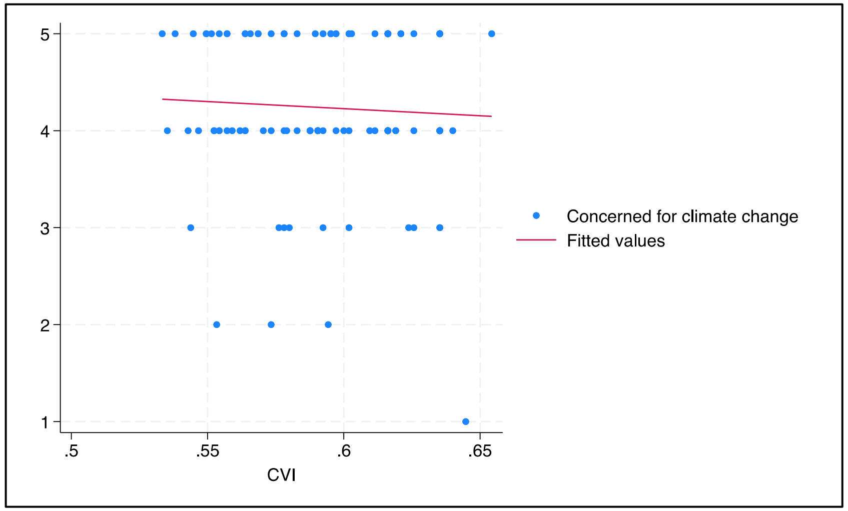

100
80
60
40
20
0
Frequency
1
1.2
1.4
1.6
1.8
2
Outside social connections to migrate

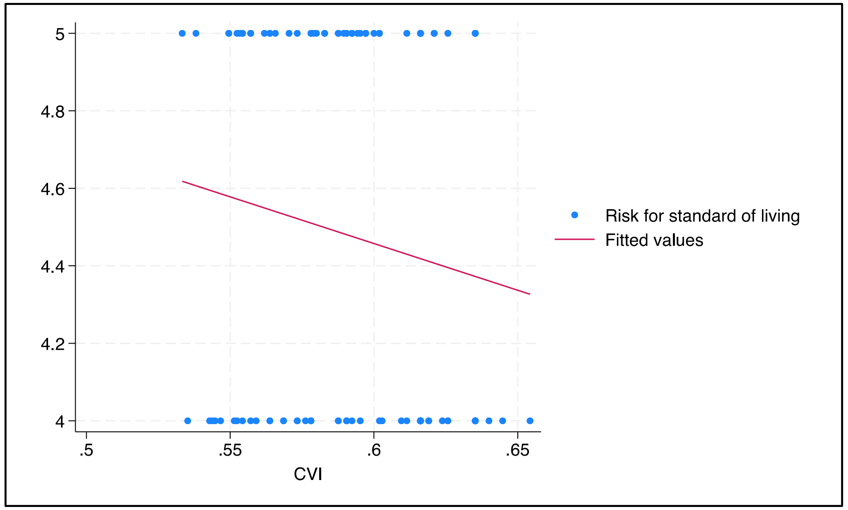
Appendix E: Extreme values

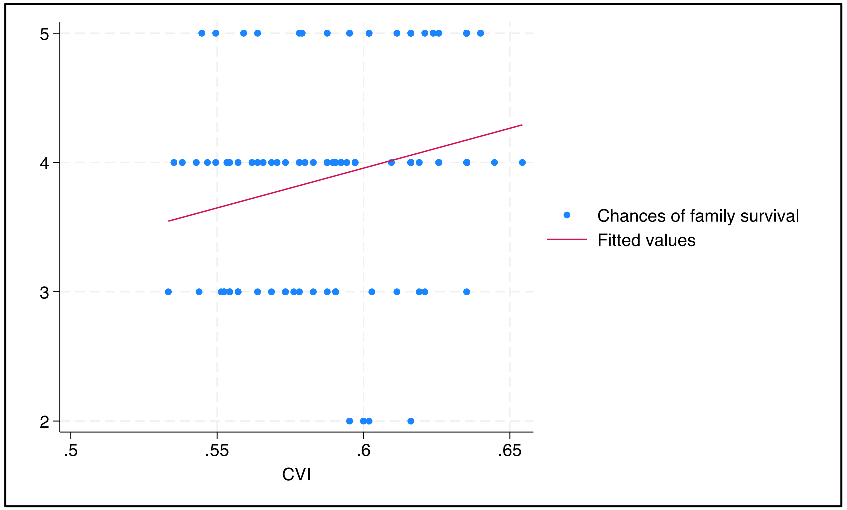
Variable	IQR	Value	Tail
Risk of climate disasters	-2.000	3.667	Lower
	-1.500	3.833	
	-1.500	3.833	
	-1.500	3.833	
Concerned for climate change	-3.000	1	Lower
	-2.000	2	
	-2.000	2	
	-2.000	2	
Bonding social capital	-3.750	0.300	Lower
	-3.500	0.333	
	-3.500	0.333	
	-3.500	0.333	
	-3.500	0.333	
	-3.250	0.367	
	-3.000	0.400	
	-2.750	0.433	
	-2.750	0.433	
	-2.500	0.467	
	-2.250	0.500	
	-2.250	0.500	
	-1.750	0.567	
	-1.750	0.567	
Age	1.765	80	Upper
Income	2.500	40000	Upper
	2.500	40000	
	3.125	45000	
	7.500	80000	

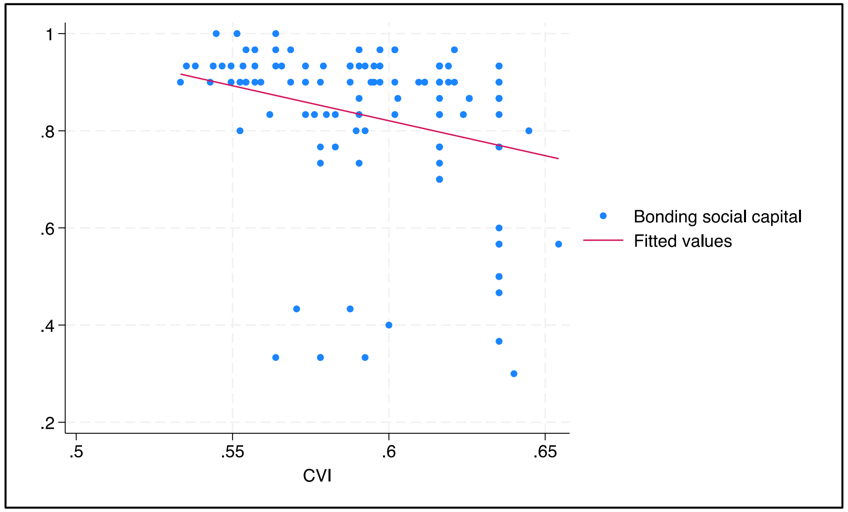
Appendix F: Scatterplots for linearity

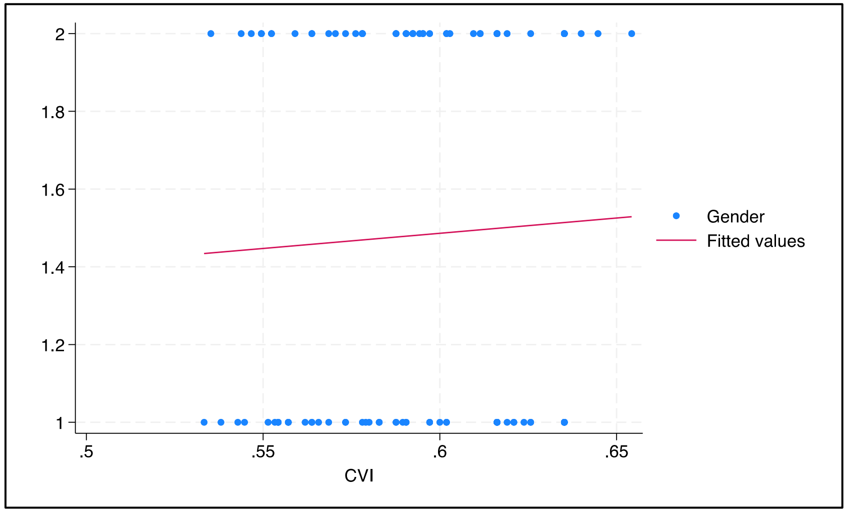


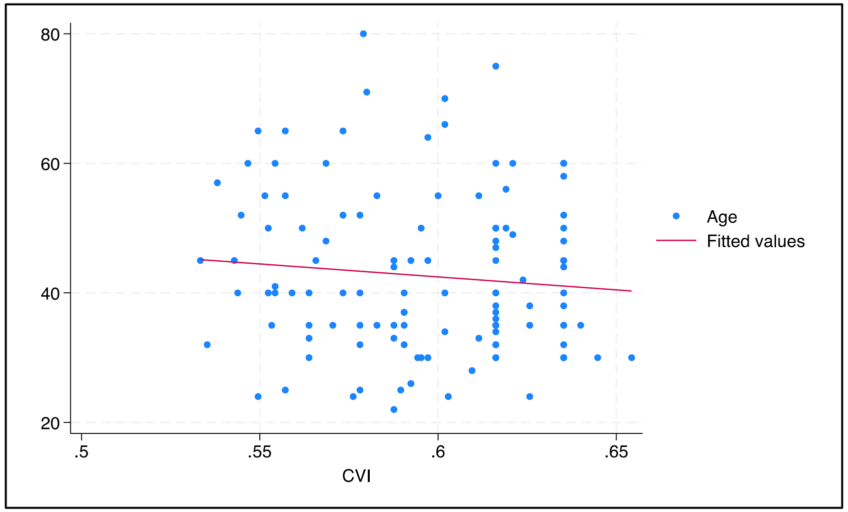


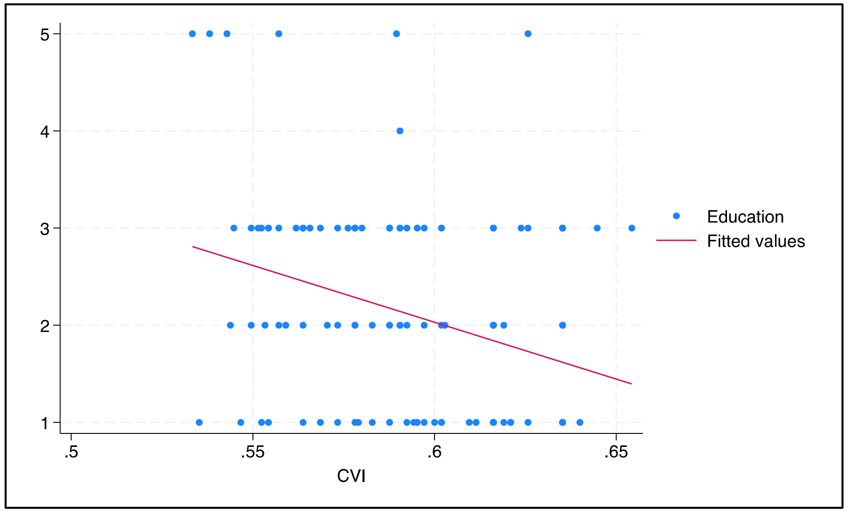


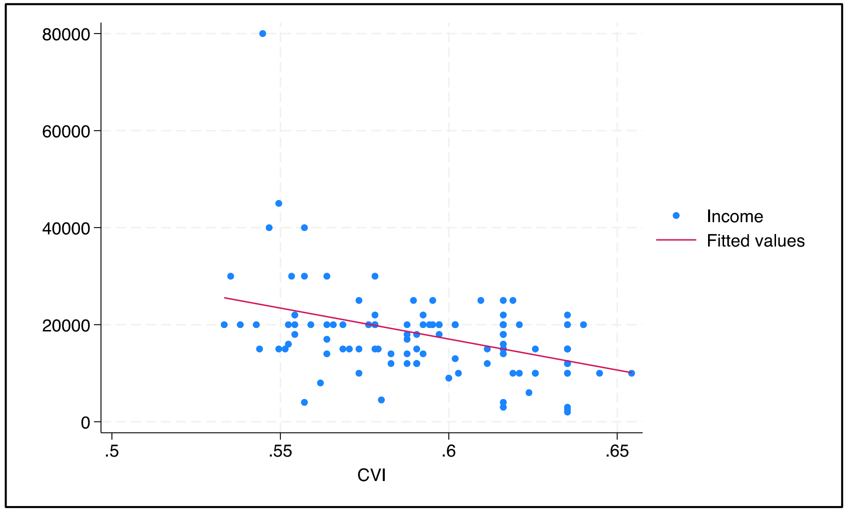


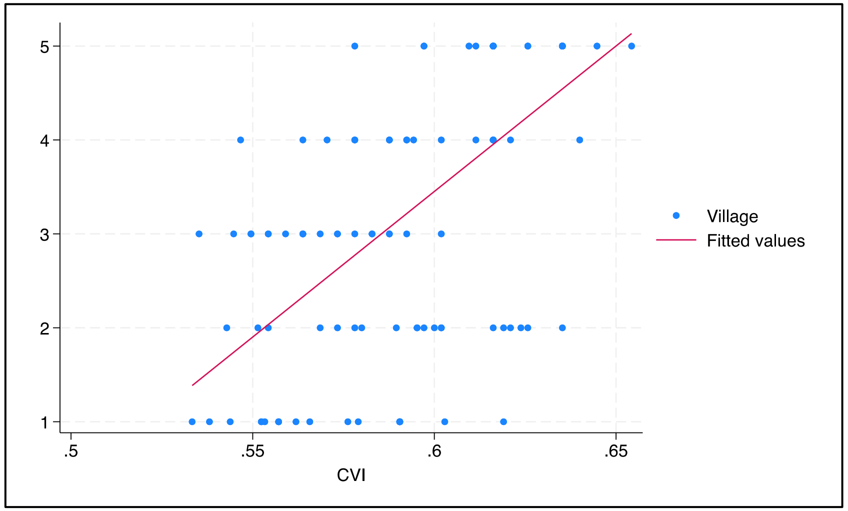

1
.8
.6
.4
.2
.5
.55
.6
.65
CVI
Bonding social capital
Fitted values

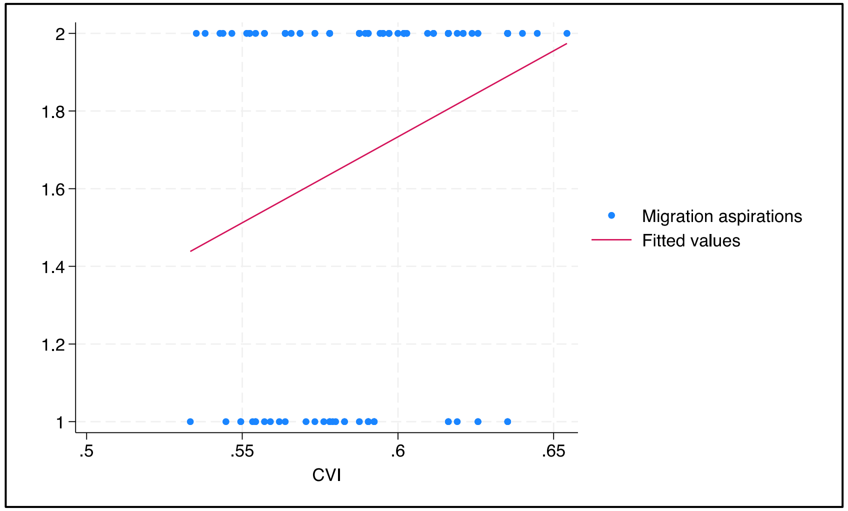

2
1.8
1.6
1.4
1.2
1
.5
.55
.6
.65
CVI
Gender
Fitted values

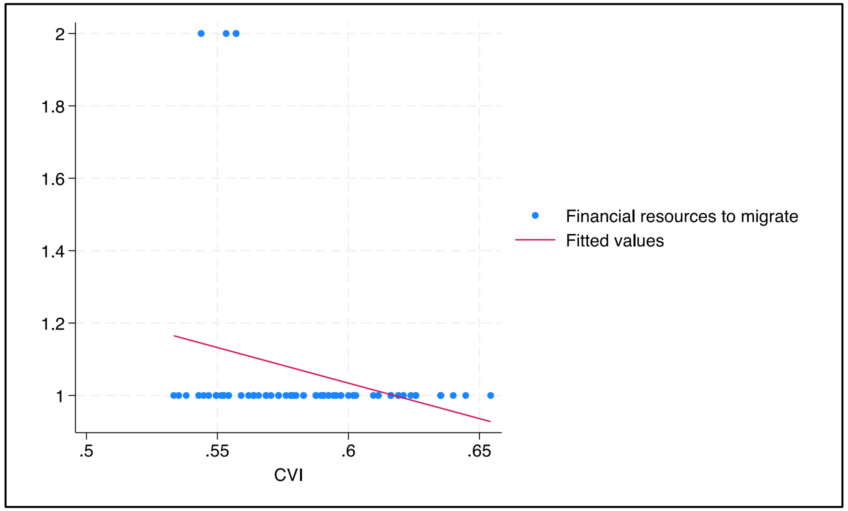

80
60
40
20
.5
.55
.6
.65
CVI
Age
Fitted values

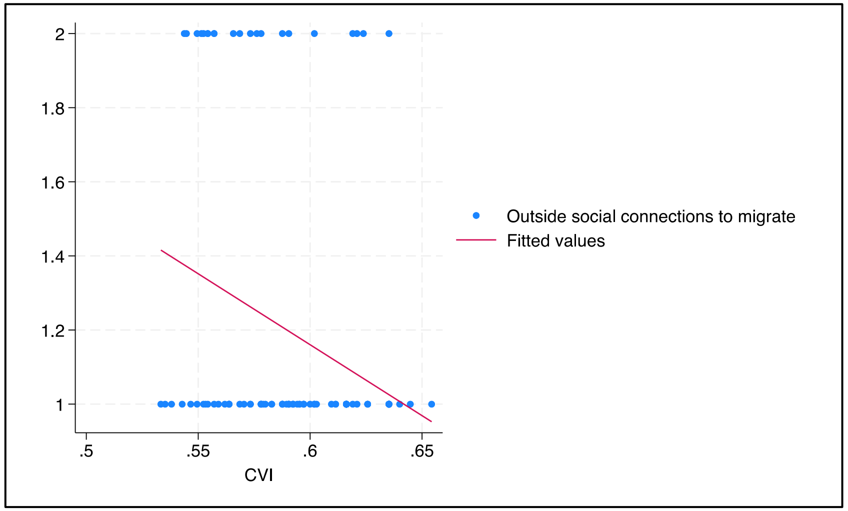

5
4
3
2
1
.5
.55
.6
.65
CVI
Education
Fitted values


80000
60000
40000
20000
0
.5
.55
.6
.65
CVI
Income
Fitted values


5
4
3
2
1
.5
.55
.6
.65
CVI
Village
Fitted values


2
1.8
1.6
1.4
1.2
1
.5
.55
.6
.65
CVI
Migration aspirations
Fitted values


2
1.8
1.6
1.4
1.2
1
.5
.55
.6
.65
CVI
Financial resources to migrate
Fitted values


2
1.8
1.6
1.4
1.2
1
.5
.55
.6
.65
CVI
Outside social connections to migrate
Fitted values

Appendix G: Shapiro-Wilk test for normality

Variable	P-value
CVI	0.004
Risk of climate disasters	0.658
Concerned for climate change	0.000
Risk for standard of living	0.999
Chances of family survival	0.077
Bonding social capital	0.000
Age	0.001
Education	0.000
Income	0.000
Village	0.440
Migration aspirations	0.148
Financial resources to migrate	0.000
Outside social connections to migrate	0.000

Normality is present if p>0.05

Appendix H: Variance Inflation Factors (VIFs) for multicollinearity

Variable	VIF	1/VIF
Risk of climate disasters	1.48	0.675
Concerned for climate change	1.48	0.678
Risk for standard of living	1.38	0.725
Chances of family survival	1.30	0.767
Bonding social capital	1.18	0.851
Gender	1.17	0.856
Age	1.14	0.878
Education	1.14	0.879
Income	1.09	0.914
Village	1.04	0.960
Migration aspirations	1.00	0.996
Financial resources to migrate	1.06	0.944
Outside social connections to migrate	1.06	0.944
Mean VIF	1.24	

Multicollinearity is present if VIF>5

Appendix I: Breusch-Pagan test for homoskedasticity

Model	Breusch-Pagan Test
Model 6	0.058
Model 8	0.089
Model 9	0.679
Model 15	0.641
Model 16	0.335
Model 17	0.790
Model 18	0.728
Model 19	0.337

Heteroskedasticity is present if $p<0.05$

Appendix J: Regression equations

Model 1

$$Climate\ Vulnerability\ Index_{it} = \beta_0 + \beta_1 Gender_{it} + \beta_2 Age_{it} + \beta_3 Education_{it} + \beta_4 Income_{it} + \beta_5 Village_{it} + \varepsilon_{i,t}$$

Model 2

$$Climate\ Vulnerability\ Index_{it} = \beta_0 + \beta_1 Risk\ of\ climate\ induced\ events_{it} + \beta_2 Gender_{it} + \beta_3 Age_{it} + \beta_4 Education_{it} + \beta_5 Income_{it} + \beta_6 Village_{it} + \varepsilon_{i,t}$$

Model 3

$$Climate\ Vulnerability\ Index_{it} = \beta_0 + \beta_1 Concerned\ for\ climate\ change_{it} + \beta_2 Gender_{it} + \beta_3 Age_{it} + \beta_4 Education_{it} + \beta_5 Income_{it} + \beta_6 Village_{it} + \varepsilon_{i,t}$$

Model 4

$$Climate\ Vulnerability\ Index_{it} = \beta_0 + \beta_1 Risk\ for\ standard\ of\ living_{it} + \beta_2 Gender_{it} + \beta_3 Age_{it} + \beta_4 Education_{it} + \beta_5 Income_{it} + \beta_6 Village_{it} + \varepsilon_{i,t}$$

Model 5

$$
\begin{aligned}
&Climate\ Vulnerability\ Index_{it} \\
&\quad = \beta_0 + \beta_1 Chances\ of\ family\ survival_{it} + \beta_2 Gender_{it} + \beta_3 Age_{it} \\
&\quad + \beta_4 Education_{it} + \beta_5 Income_{it} + \beta_6 Village_{it} + \varepsilon_{i,t}
\end{aligned}
$$

Model 6

$$
\begin{aligned}
&Climate\ Vulnerability\ Index_{it} \\
&\quad = \beta_0 \\
&\quad + \beta_1 Risk\ of\ climate\ induced\ events_{it} + \beta_2 Concerned\ for\ climate\ change_{it} \\
&\quad + \beta_3 Risk\ for\ standard\ of\ living_{it} + \beta_4 Chances\ of\ family\ survival_{it} \\
&\quad + \beta_5 Gender_{it} + \beta_6 Age_{it} + \beta_7 Education_{it} + \beta_8 Income_{it} + \beta_9 Village_{it} + \varepsilon_{i,t}
\end{aligned}
$$

Model 7

$$
\begin{aligned}
&Climate\ Vulnerability\ Index_{it} \\
&\quad = \beta_0 \\
&\quad + \beta_1 Risk\ of\ climate\ induced\ events_{it} + \beta_2 Concerned\ for\ climate\ change_{it} \\
&\quad + \beta_3 Risk\ for\ standard\ of\ living_{it} + \beta_4 Chances\ of\ family\ survival_{it} \\
&\quad + \beta_5 Bonding\ social\ capital\ index_{it} + \beta_6 Gender_{it} + \beta_7 Age_{it} + \beta_8 Education_{it} \\
&\quad + \beta_9 Income_{it} + \beta_{10} Village_{it} + \varepsilon_{i,t}
\end{aligned}
$$

Model 8

$$
\begin{aligned}
&Climate\ Vulnerability\ Index_{it} \\
&\quad = \beta_0 \\
&\quad + \beta_1 Risk\ of\ climate\ induced\ events_{it} + \beta_2 Concerned\ for\ climate\ change_{it} \\
&\quad + \beta_3 Risk\ for\ standard\ of\ living_{it} + \beta_4 Chances\ of\ family\ survival_{it} \\
&\quad + \beta_5 Bonding\ social\ capital\ index_{it} \\
&\quad + \beta_6 (Bonding\ social\ capital\ index * Risk\ of\ climate\ induced\ events)_{it} \\
&\quad + \beta_7 (Bonding\ social\ capital\ index * Concerned\ for\ climate\ change)_{it} \\
&\quad + \beta_8 (Bonding\ social\ capital\ index * Risk\ for\ standard\ of\ living)_{it} \\
&\quad + \beta_9 (Bonding\ social\ capital\ index * Chances\ of\ family\ survival)_{it} \\
&\quad + \beta_{10} Gender_{it} + \beta_{11} Age_{it} + \beta_{12} Education_{it} + \beta_{13} Income_{it} + \beta_{14} Village_{it} + \varepsilon_{i,t}
\end{aligned}
$$

Model 9

$$
\begin{aligned}
&Climate\ Vulnerability\ Index_{it}\\
&\qquad = \beta_0 + \ \beta_1 Gender_{it} + \beta_2 Age_{it} + \beta_3 Education_{it} + \beta_4 Income_{it}\\
&\qquad + \beta_5 (Gender * Age)_{it} + \beta_6 (Gender * Education)_{it} + \beta_7 (Gender * Income)_{it}\\
&\qquad + \beta_8 (Age * Education)_{it} + \beta_9 (Age * Income)_{it} + \beta_{10} (Age * Income)_{it}\\
&\qquad + \beta_{11} (Education * Income)_{it} + \varepsilon_{i,t}
\end{aligned}
$$

Model 10

$$
\begin{aligned}
&Climate\ Vulnerability\ Index_{it}\\
&\qquad = \beta_0 + \ \beta_1 Gender_{it} + \beta_2 Age_{it} + \beta_3 Education_{it} + \beta_4 Income_{it}\\
&\qquad + \beta_5 (Gender * Age * Education)_{it} + \beta_6 (Age * Education * Income)_{it}\\
&\qquad + \beta_7 (Education * Income * Gender)_{it} + \beta_8 (Income * Gender * Age)_{it} + \varepsilon_{i,t}
\end{aligned}
$$

Model 11

$$
\begin{aligned}
&Risk\ of\ climate\ induced\ events_{it}\\
&\qquad = \beta_0 + \beta_1 Gender_{it} + \ \beta_2 Age_{it} + \ \beta_3 Education_{it} + \ \beta_4 Income_{it}\\
&\qquad + \beta_5 Village_{it} + \varepsilon_{i,t}
\end{aligned}
$$

Model 12

$$
\begin{aligned}
&Concerned\ for\ climate\ change_{it}\\
&\qquad = \beta_0 + \beta_1 Gender_{it} + \ \beta_2 Age_{it} + \ \beta_3 Education_{it} + \ \beta_4 Income_{it}\\
&\qquad + \beta_5 Village_{it} + \varepsilon_{i,t}
\end{aligned}
$$

Model 13

$$
\begin{aligned}
&Risk\ for\ standard\ of\ living_{it}\\
&\qquad = \beta_0 + \beta_1 Gender_{it} + \ \beta_2 Age_{it} + \ \beta_3 Education_{it} + \ \beta_4 Income_{it}\\
&\qquad + \beta_5 Village_{it} + \varepsilon_{i,t}
\end{aligned}
$$

Model 14

$$
\begin{aligned}
&Chances\ of\ family\ survival_{it}\\
&\qquad = \beta_0 + \beta_1 Gender_{it} + \ \beta_2 Age_{it} + \ \beta_3 Education_{it} + \ \beta_4 Income_{it}\\
&\qquad + \beta_5 Village_{it} + \varepsilon_{i,t}
\end{aligned}
$$

Model 15

$$Risk\ of\ climate\ induced\ events_{it} = \beta_0 + \beta_1 Gender_{it} + \beta_2 Age_{it} + \beta_3 Education_{it} + \beta_4 Income_{it} + \beta_5 (Gender * Age)_{it} + \beta_6 (Gender * Education)_{it} + \beta_7 (Gender * Income)_{it} + \beta_8 (Age * Education)_{it} + \beta_9 (Age * Income)_{it} + \beta_{10} (Age * Income)_{it} + \beta_{11} (Education * Income)_{it} + \varepsilon_{i,t}$$

Model 16

$$Concerned\ for\ climate\ change_{it} = \beta_0 + \beta_1 Gender_{it} + \beta_2 Age_{it} + \beta_3 Education_{it} + \beta_4 Income_{it} + \beta_5 (Gender * Age)_{it} + \beta_6 (Gender * Education)_{it} + \beta_7 (Gender * Income)_{it} + \beta_8 (Age * Education)_{it} + \beta_9 (Age * Income)_{it} + \beta_{10} (Age * Income)_{it} + \beta_{11} (Education * Income)_{it} + \varepsilon_{i,t}$$

Model 17

$$Risk\ for\ standard\ of\ living_{it} = \beta_0 + \beta_1 Gender_{it} + \beta_2 Age_{it} + \beta_3 Education_{it} + \beta_4 Income_{it} + \beta_5 (Gender * Age)_{it} + \beta_6 (Gender * Education)_{it} + \beta_7 (Gender * Income)_{it} + \beta_8 (Age * Education)_{it} + \beta_9 (Age * Income)_{it} + \beta_{10} (Age * Income)_{it} + \beta_{11} (Education * Income)_{it} + \varepsilon_{i,t}$$

Model 18

$$Chances\ of\ family\ survival_{it} = \beta_0 + \beta_1 Gender_{it} + \beta_2 Age_{it} + \beta_3 Education_{it} + \beta_4 Income_{it} + \beta_5 (Gender * Age)_{it} + \beta_6 (Gender * Education)_{it} + \beta_7 (Gender * Income)_{it} + \beta_8 (Age * Education)_{it} + \beta_9 (Age * Income)_{it} + \beta_{10} (Age * Income)_{it} + \beta_{11} (Education * Income)_{it} + \varepsilon_{i,t}$$

Model 19

$$Climate\ Vulnerability\ Index_{it} = \beta_0 + \beta_1 Migration\ aspirations_{it} + \beta_2 Financial\ resources\ to\ migrate_{it} + \beta_3 Outside\ social\ connections\ to\ migrate_{it} + \varepsilon_{i,t}$$

Model 20

$$Migration\ aspirations_{it} = \beta_0 + \beta_1 Climate\ Vulnerability\ Index_{it} + \varepsilon_{i,t}$$

Model 21

$$Migration\ aspirations_{it} = \beta_0 + \beta_1 Risk\ of\ climate\ induced\ events_{it} + \beta_2 Concerned\ for\ climate\ change_{it} + \beta_3 Risk\ for\ standard\ of\ living_{it} + \beta_4 Chances\ of\ family\ survival_{it} + \varepsilon_{i,t}$$

Appendix K: Robustness tests

CVI	Model 6 Bootstrapped	Model 8 Bootstrapped
Independent variables		
Risk of climate-induced events	0.017**	0.020***
	(0.011)	(0.007)
Concerned for climate change	-0.002	-0.002
	(0.345)	(0.483)
Risk for standard of living	-0.005	-0.005
	(0.215)	(0.237)
Chances of family survival	-0.003	0.004
	(0.287)	(0.214)
Moderator variable		
Bonding social capital index (BSCI)		-0.002
		(0.352)
Interaction terms		
BSCI*Risk of climate-induced events		-0.004
		(0.719)
BSCI*Concerned for climate change		-0.003
		(0.489)
BSCI*Risk for standard of living		-0.001
		(0.891)
BSCI*Chances of family survival		-0.005
		(0.158)
Control variables		
Gender	-0.000	-0.001
	(0.974)	(0.797)
Age	-0.000	-0.000
	(0.343)	(0.261)
Education	-0.004**	-0.004**
	(0.046)	(0.048)
Income	-0.000***	-0.000***
	(0.000)	(0.000)
Village	0.009***	0.009***
	(0.000)	(0.000)
Constant	0.608***	0.611***
	(0.000)	(0.000)
R^2	0.570	0.594
Adjusted R^2	0.535	0.540
Wald χ^2	196.83***	194.21***
N	120	120
Replications	1,000	1,000

CVI	Model 9 Bootstrapped
Independent variables	
Risk of climate-induced events	0.017**
	(0.030)
Concerned for climate change	-0.003
	(0.299)
Risk for standard of living	-0.005
	(0.259)
Chances of family survival	0.002
	(0.494)
Interaction terms	
Gender*Age	-0.001
	(0.191)
Gender*Education	-0.004
	(0.452)
Gender*Income	-1.03e-06
	(0.184)
Age*Education	-0.0004**
	(0.016)
Age*Income	7.84e-09
	(0.766)
Education*Income	-1.61e-08
	(0.961)
Control variables	
Gender	0.048*
	(0.055)
Age	0.001*
	(0.078)
Education	0.017
	(0.172)
Income	-5.14e-07
	(0.797)
Village	0.010***
	(0.000)
Constant	0.511***
	(0.000)
R^2	0.608
Adjusted R^2	0.552
Wald χ^2	239.58***
N	120
Replications	1,000

Risk of climate-induced events	Model 11 Bootstrapped
Independent variables	
Gender	-0.110**
	(0.034)
Age	-0.002
	(0.383)
Education	-0.021
	(0.444)
Income	-7.22e-06*
	(0.077)
Constant	4.854***
	(0.000)
R^2	0.070
Adjusted R^2	0.038
Wald χ^2	10.28**
N	120
Replications	1,000

Chances of family survival	Model 14 Bootstrapped
Independent variables	
Gender	-0.066
	(0.660)
Age	-0.011*
	(0.076)
Education	-0.069
	(0.254)
Income	9.48e-07
	(0.925)
Constant	4.626***
	(0.000)
R^2	0.026
Adjusted R^2	-0.008
Wald χ^2	3.95
N	120
Replications	1,000

Concerned for climate change	**Model 16 Bootstrapped**
Independent variables	
Gender	-0.300
	(0.761)
Age	0.007
	(0.802)
Education	0.085
	(0.849)
Income	-0.000*
	(0.206)
Interaction terms	
Gender*Age	-0.005
	(0.757)
Gender*Education	-0.153
	(0.389)
Gender*Income	0.000
	(0.248)
Age*Education	-0.007
	(0.251)
Age*Income	6.88e-07
	(0.594)
Education*Income	0.000**
	(0.083)
Constant	5.586***
	(0.001)
R^2	0.090
Adjusted R^2	0.007
Wald χ^2	8.71
N	120
Replications	1,000

CVI	**Model 19 Bootstrapped**
Migration aspirations	0.018***
	(0.001)
Financial resources to migrate	-0.034***
	(0.000)
Outside social connections to migrate	-0.019***
	(0.007)
Constant	0.622***
	(0.000)
R^2	0.218
Adjusted R^2	0.198
Wald χ^2	56.04***
N	120
Replications	1,000

Migration aspirations	**Model 20 Bootstrapped**
CVI	4.423***
	(0.001)
Constant	-0.923
	(0.245)
R^2	0.087
Adjusted R^2	0.079
Wald χ^2	11.41***
N	120
Replications	1,000

Migration aspirations	**Model 21 Bootstrapped**
Risk of climate-induced events	0.121
	(0.382)
Concerned for climate change	0.089
	(0.123)
Risk for standard of living	-0.147*
	(0.062)
Chances of family survival	0.012
	(0.831)
Constant	1.410*
	(0.042)
R^2	0.054
Adjusted R^2	0.021
Wald χ^2	7.34
N	120
Replications	1,000