ADAPTING TO UNCERTAINITIES: ASSESSING THE IMPACTS OF DAMS, CLIMATE CHANGE, AND RESOURCE SHIFTS ON FARMING LIVELIHOODS IN THE LOWER MEKONG REGION

By

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ABSTRACT

The Lower Mekong region (LMR) is experiencing rapid social-ecological changes due to infrastructure development and climate change. The construction of dams along the Mekong River and its tributaries has triggered significant biophysical alterations, including changes in water flow, nutrient cycling, and sediment exchange. These changes have profound implications for the 86 percent of the Lower Mekong Basin (LMB) population who rely on the river for their livelihoods, primarily in agriculture and fisheries. Besides, the region faces an increasing frequency of extreme climate events, particularly droughts and floods. These combined pressures have heightened the vulnerability of resource-dependent communities, further exacerbated by unjust resource governance that often marginalizes them.

This dissertation explores the multifaceted challenges faced by resource-dependent communities in the LMR, with a particular focus on their responses to the uncertainties driven by dams, climate change, and resource shifts. The study hypothesizes that most noticeable changes are occurring at the household level, influenced by their perceptions of climate risk and their capacity to access and utilize vital livelihood resources. These shifts exert pressures on land and watershed ecosystems, raising concerns over the sustainability of critical ecosystem services. Adopting a mixed-method approach, this research unfolds across three chapters:

Chapter 1 assesses the impacts of dams on various livelihood resources in downstream farming communities at different distances from affected rivers, using unbalanced panel data analysis. The findings reveal a decrease in natural and financial resource accessibility, alongside a positive effect on physical resource accessibility post-dam construction. Communities closer to dams (<10 km) experience more pronounced negative effects on natural resources, while financial resource access improves for those within 20 km. Physical resources show spatial improvements, primarily within 10 km. Although no temporal effects are observed for social resources, spatial effects indicate reduced accessibility near dams. However, communities nearby irrigation dam experience increased social resource access post-dam construction. These findings highlight the spatial and temporal variations in resource impacts, emphasizing key areas for improving Environmental Impact Assessments (EIAs) and adaptation strategies to better support downstream ecosystems and communities.

Chapter 2 delves into drought risk perceptions among households in irrigated and flood-pulse communities, exploring the factors explaining variations in risk perception at both

household and community levels. Utilizing a mixed-effects model alongside qualitative information from interviews and observations, this chapter reveals the significance of psychological and socio-economic factors, including households' knowledge of drought, perceived ability, affiliation with various organizations, and wealth condition, shaping risk perception. These findings suggest the development of context-tailored risk communication and management strategies, enhancing the adaptive capacity of vulnerable communities.

Chapter 3 examines the role of perceived peer effect and formal networks in shaping farmers' adaptive behaviors using influence network modeling. The findings suggest the need for leveraging both formal and informal networks, increasing knowledge about drought and improving economic conditions to build farmers' capacity to navigate climate-related challenges and adopt practices that ensure the sustainability of resource-dependent farming communities in Cambodia and beyond.

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INTRODUCTION

Climate change is arguably the greatest challenge facing the world today, with widespread and far-reaching impacts across various sectors including global water systems, agricultural production, human health, and energy resources. Its effects on river ecosystems are particularly complex and uncertain, further complicating water resource management (Ficklin et al., 2013). Human-induced climate change is expected to alter the hydrological regimes of numerous river systems, influencing water flow and sediment flux (Nguyen & Tran, 2024; B. Shrestha et al., 2013).

Water infrastructure projects, such as dams, offer adaptation opportunities to meet the growing water demands for irrigation, industrial, and domestic consumption, while also playing a crucial role in energy production. Hydroelectric power is the largest source of renewable energy, accounting for 68 percent of the renewables, more than twice all other renewables combined (Barasa Kabeyi & Akanni. Olanrewaju, 2023). In addition to its energy benefits, hydroelectric power has a minimal carbon footprint and supports ecosystem services, such as water retention and soil conservation. However, while dams and reservoirs are viewed as instruments of economic gain and water security by many developing governments, their unprecedented development has significant impacts on ecosystems and rural livelihoods, particularly in the lower reaches of these structures (Beck et al., 2012).

The Mekong River, a transboundary waterway in Southeast Asia, exemplifies these complex dynamics. The river is characterized by its unique and interconnected hydrological, ecological, and agricultural systems, which supported the livelihoods of approximately 65 million people (MRC, 2019). The upper region of the Mekong includes China and Myanmar, while the Lower Mekong Region (LMR) comprises Thailand, Lao PDR, Cambodia, and Vietnam. In the LMR, about 75% of the inhabitants rely on agriculture, which depend on seasonal rainfall, flood-replenished soils, and fisheries from rivers and lakes (Pokharel et al., 2018).However, these systems are increasingly at risk due to climate change, extensive dam construction, and land-use changes.

Given the LMR’s sensitivity to climate extremes and disasters, particularly droughts and floods, the region is highly vulnerable to temperature increases and variations in seasonal rainfall (MRC, 2019b). Furthermore, unclear governance structures for water resource management, coupled with land-use changes, threaten ecosystem health and resilience, potentially exacerbating water and food scarcity at the local level (Eastham et al., 2008). As farmers and fishers adapt, their changing livelihood practices, including resource utilization, may further strain watershed ecology and ecosystem services (Piesse, 2016).

This dissertation explores the multifaceted challenges faced by resource-dependent communities and households in the Lower Mekong Region, focusing on their perceived risks and responses to uncertainties driven by dams, climate change, and resource shifts. Through a mixed-method approach, this research addresses these issues across three chapters (overview in Table 1), each focusing on different but interconnected aspects of the problem.

Chapter 1 explores the study context by examining the relationship between dam construction and shifts in livelihood resources. It lays the foundation for the research by identifying critical resources—natural, social, physical, and financial—that are significantly impacted post-dam, affecting downstream communities in heterogeneous ways. By analyzing both spatial and temporal effects of dams on communities beyond 10 km from the impacted river sections, this chapter highlights dimensions of dam-related impacts on diverse livelihood resources that are often overlooked in studies focusing on the social effects of dam construction. The findings address the need for a more comprehensive understanding of how resource-based uncertainties, compounded by climate risks, shape household vulnerabilities in these regions.

Chapter 2 shifts the focus from dam-induced changes to household perceptions of drought risk, maintaining the shared emphasis on water as a critical resource—whether controlled by dams or threatened by drought conditions. This chapter contributes to the limited literature on drought risk perceptions within complex hydro-agricultural-fisheries systems, where institutional support is often lacking. By exploring the variation in drought risk perception at both household and community levels, it examines how biophysical, psychological, socio-economic, and demographic factors shape these perceptions. The findings provide a deeper understanding of how farmers interpret and respond to climate uncertainties, particularly within the evolving resource landscape outlined in Chapter 1.

Finally, **Chapter 3** explores household adaptation decisions in relation to social networks, a critical resource impacted by dams (Chapter 1) and an important factor in shaping risk perceptions (Chapter 2). This chapter expands on the limited research concerning how perceived peer influence affects farmers' adaptive behaviors, particularly in regions with limited institutional support. It specifically examines the role of both informal peer influence and formal networks in shaping adaptation decisions, while also considering other socio-economic, psychological, and experiential factors related to climate extremes. By addressing these interconnected factors, the chapter deepens our understanding of the social dynamics that influence adaptation in vulnerable farming communities.

Together, these chapters provide the importance of considering both individual and community level factors when addressing the challenges posed by resource shifts and climate variability in the Lower Mekong Region.

Table 1: Research Framework: Objectives, Methods, and Contributions to dissertation goal

Objectives	**Study population**	**Methods**	**Contribution to dissertation goal**
Chapter 1: Assess the spatial and temporal impact of dams on downstream communities' access to diverse livelihood resources	Farming communities downstream to the multiple dams in Cambodia	Unbalanced mixed effect modeling at community level	Identifies the key resources, particularly natural, social, and financial, affected by dam construction, providing insights into resource-based uncertainties faced by farming households
Chapter 2: Identify key bio-physical, socio-economic, psychological factors shaping drought risk perception and explore the pattern of drought severity by community type	Households situated in the irrigated and flood-pulse communities, Cambodia	Mixed effect modeling at household level and qualitative approach including narratives from informal interviews and causal loop diagram at community level	Reveals how household perceived drought risk based on individual and drought characteristics in the context of irrigation dams and changing flood-pulse dynamics of Tonle Sap Lake

Table 1 (cont'd)

Chapter 3 Examine the effect of perceived peer influence and informal networks in shaping farm households' adaptive behaviors	Rice farming households, Cambodia	Network influence modeling at household level and qualitative approach including thematic coding and narratives from informal interviews and observations	Explains social dynamics and decision-making processes underlying farmers' responses to resource shifts and climate extremities, considering socio-economic, psychological, and experiential factors

The dissertation chapters used a case of Cambodia, which is relevant given its unique position in the LMB. Approximately 86 percent of Cambodia's territory lies within the Mekong Basin, making it heavily reliant on the river for water-related economic activities and domestic supply (Sithirith, 2021) . The Mekong and its connected Tonle Sap system are crucial for Cambodian livelihoods, providing essential resources for agriculture, fisheries, and urban development. Rainfed agriculture, which supports around 63 percent of Cambodia's population, contributes 22 percent of the nation's GDP as of 2022 (MoP, 2022). In addition, freshwater fish from the Mekong system provide up to 80 percent of the animal protein consumed in Cambodia, underscoring the river's pivotal role in ensuring food security (Hortle, 2007).

The Tonle Sap, Southeast Asia's largest lake, acts as a natural flood buffer and supports vital fisheries and floodplain agriculture (Manohar et al., 2023). However, Cambodia's downstream position and its dependence on the Mekong's seasonal flood pulse make the country particularly vulnerable to disruptions in the river's hydrology (Morton & Olson, 2018). This vulnerability is compounded by Cambodia's limited resources and knowledge to effectively adapt to environmental changes. As such, Cambodia serves as a prime example of the complex interplay between resource dependency, climate vulnerability, and development challenges in the LMB, making it an ideal focus for this research.

CHAPTER I: THE SPATIAL-TEMPORAL IMPACT OF DAMS ON DOWNSTREAM COMMUNITIES' RESOURCE ACCESSIBILITY: CASE STUDIES FROM CAMBODIA

1.1 Introduction

In recent decades, dam construction has been prioritized in order to meet energy demands, support agricultural production, and foster industrial growth. Dams can mitigate drought conditions, control downstream flooding, and provide a year-round water supply by inundating upstream wetlands and riparian areas (Mulligan et al., 2020). Acknowledging these multiple benefits, many governments, particularly in the Global South, view dams as instruments for economic gain, water security, and poverty reduction (Wang et al., 2022).

However, the rapid development of dams has raised concerns regarding their effects on hydro-ecology and dependent rural livelihoods, particularly for farmers and fishers in the lower reaches of these structures (Beck et al., 2012). For instance, studies have shown that dams can significantly alter river ecosystems, affecting fish migration patterns, sediment transport, and water quality, potentially leading to fish population declines and impacts on both commercial and subsistence fisheries (Arantes et al., 2022).

While dams can enhance agricultural productivity through irrigation, they may also lead to changes in downstream water quantity and quality, potentially affecting traditional farming practices. Further, there is great uncertainty over the ability of dams to manage water demand under forecasted climate scenarios, with concerns of inducing drought (Di Baldassarre et al., 2018; S. Huang et al., 2021). The social impacts of dams, including displacement of communities, changes in local economies and cultural values, add more complexity to their assessment (Castro-Diaz et al., 2023; Fung et al., 2019; Richter et al., 2010). This all holds true for dams in Lower Mekong Region (LMR).

Dams in the LMR

Dam construction has been a national priority to LMR countries to spur economic growth while supporting food and energy security. The regional population is expected to grow by as much as 45 percent over two decades, with a projection of 15 to 25 percent by 2030 at the national level (Pokharel et al., 2018). Parallelling this growth, agricultural land expansion of 19-63 percent is anticipated, increasing water and energy demands and driving the planning of numerous dam projects along various reaches of the Mekong mainstream and its tributaries.

Recent studies suggest an unprecedented construction of dams, in total 1,055 in the Mekong including 608 hydropower dams and 447 non-hydropower dams for flood control, water supply, and irrigation (Ang et al., 2023). Hydropower projects from 1 MW and 4,200 MW have led to a dramatic increase in hydropower capacity from 1,242 MW in the 1980s to 69,199 MW post-2020s. Considering only 59 hydropower dams constructed before 2015, gross national economic value increased by around 265 percent (MRC, 2019b). Enticed by such financial incentives, most LMB countries, particularly Cambodia and Lao PDR, facing limited economic opportunities, are encouraged to develop an additional large-scale dams, with highest projected growth post-2020s (+18,223 MW) (Ang et al., 2023).

As a developer and investor, China has been involved in this unprecedented rise in dam construction. Through its Belt and Road Initiative (BRI) and other investment channels, China has heavily invested in hydropower infrastructure across Southeast Asia (Urban et al., 2013; Wouters et al., 2024). Numerous of these initiatives are a part of China's broader strategy to safeguard energy resources and advance regional economic integration (Ganeshpandian, 2024). For countries like Laos and Cambodia, Chinese investments offer critical financial support to meet their growing energy demands and economic development goals (Kuik & Rosli, 2023; Siciliano et al., 2016). However these investments also raise concerns about fair resource distribution among communities and environmental sustainability (Soukhaphon et al., 2021a).

Large water storage structures, such as dams and reservoirs, are expected to increase water and energy consumption in the region. This growth in demand will, in turn, place additional pressure on land and water resources (Smajgl & Ward, 2013). The situation is made worse by increased climate risks and unclear governance structures for water resource management, leading to inequitable resource distribution across communities. In response, community members are likely to modify farm livelihoods including farming practices and resource utilization, furthering pressure on aquatic ecosystems and their services (Siciliano et al., 2015).

Piesse (2016), for example, observed many households increasingly relying on nearby forests for income after losing agricultural land. Similarly, lower fish stocks compel riverine communities to shift their dietary practices. Furthermore, Pokharel *et al.* (2018) found evidence of large-scale forest conversion to agricultural and pastureland, with increases of 10% and 16% respectively between 1992-2015 in the Mekong Basin. The rising trend of sand mining, as observed by Robert (2017) in Vietnam's Mekong Delta, poses additional risks to riverbed stability and sediment flow. These changes have raised grave concerns over the sustainable use of water resources and the continued provision of ecosystem services to the people in the region, prompting the need for a better understanding of the socio-economic impacts of dams.

Existing research and policy gaps

The impacts of dams on hydro-ecological systems have been extensively studied in the LMR and other parts of the world. Numerous studies have documented changes in water levels, nutrient and sediment transport, soil and water quality degradation, and aquatic habitat deterioration, all of which affect freshwater vertebrates, fish diversity and populations (Bussi et al., 2021; Kuriqi et al., 2021; J. Li et al., 2013; Maavara et al., 2020; Soukhaphon et al., 2021). However, there remains a significant gap in understanding the social impacts of dams on affected communities over time and across spatial dimensions (Kirchherr et al., 2016).

Existing studies have focused on various aspects of livelihoods such as agricultural production and income, health (Dillon and Fishman, 2019), social cohesion (Fung et al., 2019), labor and migration (Calvi et al., 2020), and structural and cognitive aspects of social capital (Mayer et al., 2022). However, these studies have concentrated on resettled and host communities, neglecting the impacts on downstream, resource-dependent communities. Further, the spatial extent of these studies is often limited to areas within a few kilometers of the dam site. Some exceptions include a study by Owusu et al. (2019) who examined the Bui dam's post-dam effect on fisheries, farming and other livelihoods among downstream communities extending up to 30 km below the dam. Additionally, Fan *et al.* (2022) conducted a global study that found differential impacts of hydropower dams on greenness, population, economies, and other measures across communities at different impact zones, ranging from less than 5 km to 50 km.

While some studies have captured temporal dynamics of dam-induced impacts on different livelihoods, they often fail to provide a comprehensive assessment of all livelihood resources post dam construction. Arthur *et al.* (2020) captured locals' responses to changes in different livelihood capitals after the construction of the Bui dam. Similarly, a study by Castro-Diaz *et al.* (2023) reported the positive and negative effects of hydropower dams on natural, social, human, financial, and physical capital. However, both studies did not empirically test the temporal aspects of those effects.

Many Environmental Impact Assessments (EIAs) for dam projects fail to adequately assess downstream effects, cumulative impacts, and the full range of socio-economic consequences (Richter et al., 2010). While they often focus on upstream areas and resettled populations, they frequently overlook downstream communities that depend on river ecosystems for their livelihoods. This gap is concerning, as communities far from dam sites still experience significant disruptions to fisheries, agriculture, and water access (Moore et al., 2010).

This issue is particularly relevant in the Mekong region, where EIAs often neglect transboundary impacts on downstream communities (Soukhaphon et al., 2021a). While upstream areas may receive compensation, those downstream are frequently excluded from assessments (Kirchherr et al., 2016). Furthermore, EIAs tend to focus narrowly on environmental factors without adequately considering how dam projects affect different dimensions of livelihoods—such as natural, financial, social, human, and physical capital—which limits policymakers' understanding of the full socio-economic consequences (Baird & Frankel, 2015).

In response to these shortcomings in existing policy and research, this study seeks to examine the spatial and temporal impacts of dam impacts on accessibility to diverse livelihood resources.

Research Question and Hypotheses

Our central research question is how resource accessibility varies across downstream communities at different impact zones (i.e., space) over time (i.e., pre- and post-dam construction)? In our study, "impact zone" refers to areas at different proximities to dammed rivers and therefore likely experiencing different environmental and socio-economic changes. "Resource accessibility" refers to the ability of farming communities to access and utilize various resources namely natural, physical, social, human, and financial capital to support their livelihoods.

Specifically, we tested the following hypotheses (Figure 1):

H1: Resource accessibility changes significantly over time among downstream communities with variation observed in both pre- and post-dam periods.

H2: Proximity to dams significantly influences resource accessibility with closer communities experiencing greater disparities and more pronounced changes in resource accessibility compared to those located farther away.

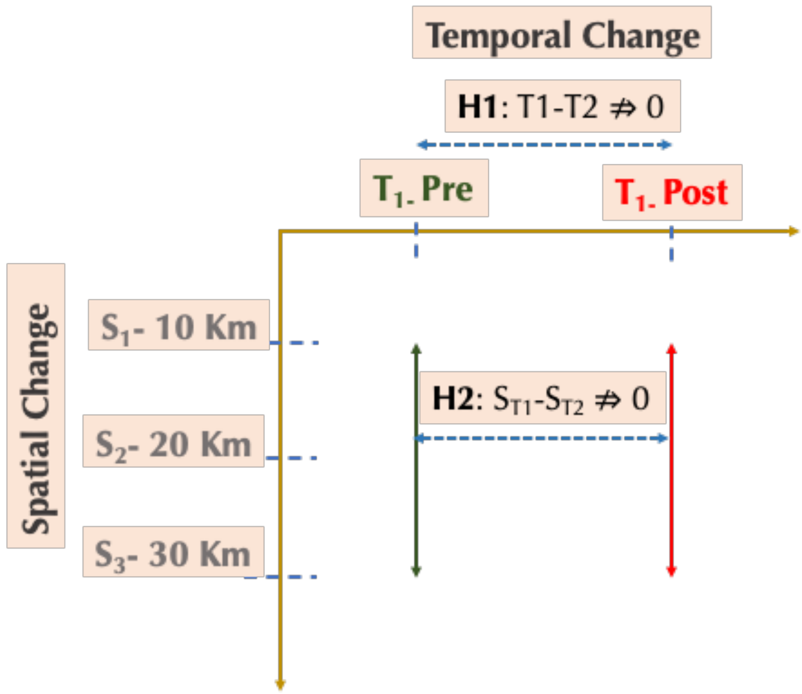


Figure 1: Visualization of the research hypothesis

1.2 Materials and method

1.2.1 Theoretical Framework: Sustainable Livelihood Framework (SLF)

The Sustainable Livelihood Framework (SLF) provides a theoretical structure for examining the complex impacts of dams on community livelihoods across spatial and temporal dimensions. This widely used framework assesses key livelihood components and contextual factors, including internal and external influences (also known as vulnerability context), which shape livelihood decisions and outcomes. The SLF is particularly relevant to our study as it helps explain how combinations of diverse livelihood resources (also called capital assets) enable households and communities to adopt various livelihood strategies such as cultivation, inland fishing, aquaculture, diversification, and migration, in response to changing environmental conditions. Access to and the transformation of these resources into different livelihood strategies are critical determinants of farm households' adaptive capacity (Sok & Yu, 2015).
In our study, we emphasize livelihood resources, not only the resources that support farmers' and fishers' livelihoods but those enabling control and agency within a system influenced by state, market, and civil organizations (Allison & Ellis, 2001; Bebbington, 1999; Scoones, 1999). Adopting this framework (Allison & Ellis, 2001; Bhandari, 2013), our study focuses on changes in access to five types of livelihood resources in the context of dam construction and operation:

Natural: This includes stocks of natural resources such as land, water, forests, and fish, which are critical for resource-dependent populations. Maintaining these assets at sustainable levels is crucial for long-term livelihood security (Reed et al., 2013). Dams can significantly alter these resources, affecting their quantity and quality across different spatial zones.

Physical: Basic infrastructure like roads, markets, water supply systems, schools, and banks build communities' capacity to reduce social and environmental vulnerability (Bebbington, 1999; Y. He & Ahmed, 2022; Scoones, 1999). Dam projects often introduce new infrastructure, potentially changing access patterns across impacted areas.

Financial: Measured in terms of cash, credit/debt, and savings, financial resources are essential for pursuing livelihood strategies. Dam construction can alter local economies, affecting income sources and financial stability in various ways across different communities.

Human: Encompassing household labor, skills, knowledge, and health, human capital enables participation in discussions and negotiations, influencing development discourses (Bebbington, 1999). Dams can enhance education and foster the development of new skills by creating new social and physical infrastructure, which can vary across different spatial and temporal scales.

Social: Comprising networks (formal and informal) and associations, social capital supports building trust and reciprocity, enhancing access to resources and adaptive capacity (Adger, 2003). Dam projects can disrupt or create new social structures, potentially altering community resilience and livelihood security.

1.2.2 Study area

Relying on Cambodia’s Agricultural Census Data from 2014 and 2019, we considered only dams that were constructed and commissioned between 2013 and 2019. Based on this criterion, we identified three dams from the dataset of the Dams of the Greater Mekong (Mekong Region Futures Institute, 2020): the Ajhang, Battambang, and Lower Sesan 2 dams (Figure 2). Table 2 provides the brief overview of dams.

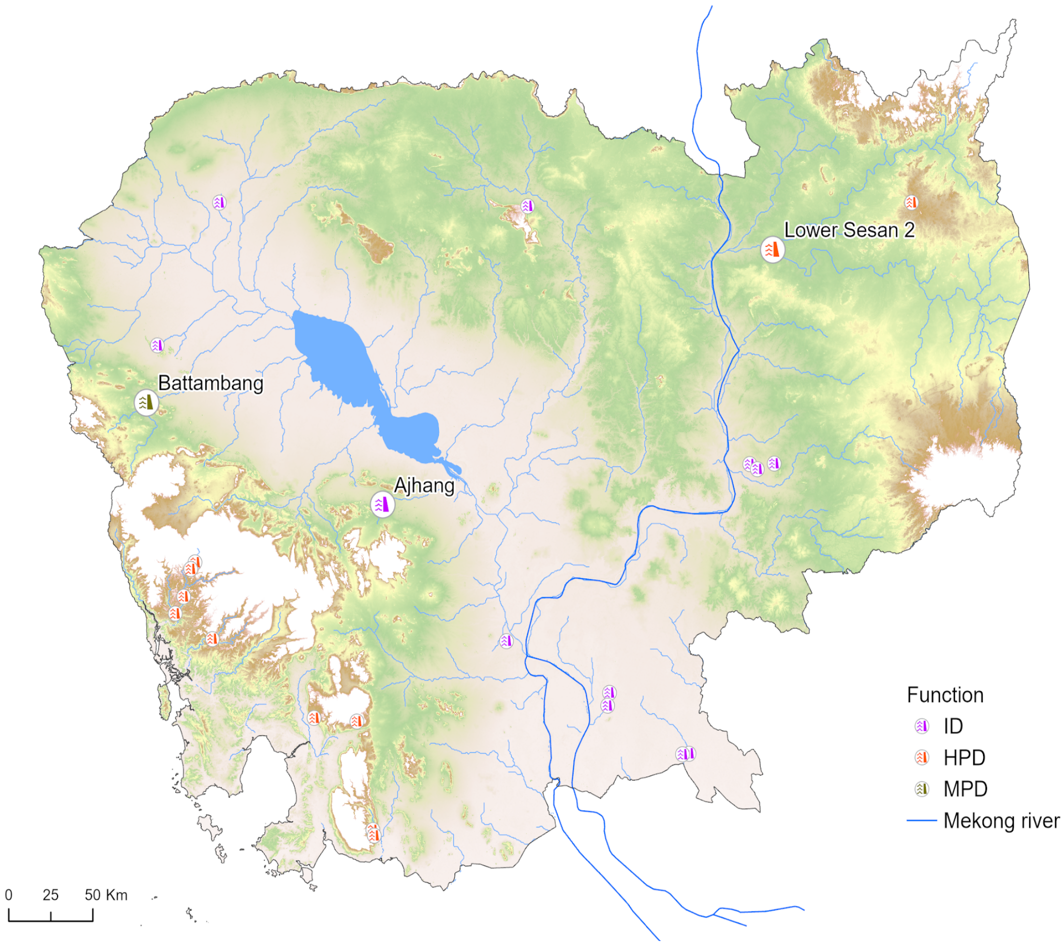


Figure 2: Study dam sites

Table 2: Dam description

Dams	Description
Ajhang	Ajhang dam, located in Kampong Chhang Province, Cambodia, was constructed between 2014 and 2018 by the Ministry of Water Resources and Meteorology, with funding from the Chinese government. Situated 41 km from the city and 120 km northwest of Phnom Penh, it lies 22.4 km away from the highway. The primary aim of the project was to irrigate 10,300 hectares of land along the left bank of the river, achieved through the construction of the main and branch canals. Additionally, the dam facilitates diversion and junction activities, featuring elements like entrance gates, drainage brakes, and connectors between the left and right banks. The dam stands at a height of 28 meters and utilizes undershot water gates. However, concerns arise due to the absence of a fish pass and the fast, shallow flow over the spillway. The catchment area for the dam is the Stung Baribour river. Source: Green *et al.* (2019)
Battambang	Battambang is a multipurpose dam, constructed between 2014 and 2018. It serves various functions including hydropower generation, irrigation system enhancement, flood control, and water supply to Battambang city. Located in Ratanak Mondul district's Plov Meas commune, it stands at a height of 49.5 meters, creating a reservoir capable of storing 286 million cubic meters of water. With the Sangke River as its catchment area, the dam facilitates water distribution through main and sub-canals. This infrastructure supports the irrigation of 47,000 hectares of wet paddy and 12,000 hectares of dry paddy across three districts: Ratanak Mondul, Banan, and Mong Russey. In terms of power generation, the dam boasts an installed capacity of 24 MW, contributing to an annual energy production of 123 GW. Source: Vida (2017)

Table 2 (Cont'd)

Lower Sesan 2	The Lower Se San 2 Dam, a hydropower dam, was constructed between 2014 and 2017 on the Se San River in Stung Treng Province. With an installed capacity of 480 MW and an average annual energy production of 2311.8 GW, it stands at a height of 45 meters. Located 25 kilometers east of Stung Treng city, its construction and operation have significant environmental and social impacts. It is estimated to displace up to 5,000 people and affect the livelihoods of over 38,675 individuals, including indigenous communities. Furthermore, the dam is likely to disrupt fish migrations, impacting fisheries resources for approximately 78,000 people living in the vicinity. Source: Sifton, (2021)

Sampling population Previous works (e.g., Lin and Qi (2019)), estimated the maximum impact of dams on nearby land use and land cover in the upper and lower Mekong River to be within 5 kilometers on average. However, Richter *et al.* (2010) argue that impacts may extend further downstream, reaching up to 10 kilometers. Expanding this perspective to the global south context, Fan *et al.* (2022) considered the impacts of hydropower dams, focusing on changes to population, urban development, greenness, and GDP, finding significant effects within a radius of 50 kilometers from dam sites, with the most notable changes occurring within 5 to 20 kilometers.

Given these findings, we selected a 20-kilometer downstream river section (referred as "impacted river segment") to evaluate the impacts of dams on downstream communities. While this acknowledges the immediate effects of dam construction on the surrounding ecosystem, we anticipated substantial shifts in various livelihood resources including natural, social, human, economic, and physical resources, beyond the dams' immediate vicinity.

We used a systematic approach to identify potential villages located downstream of each dam (unit of analysis) (Figure 3). Using ArcGIS Pro, we began by applying the "Track Downstream" geoprocessing tool to identify the river segments extending from each dam. This approach aligns with techniques used in dam break analysis and flood inundation mapping studies, where tools like HEC-GeoRAS are employed to process geospatial data for hydraulic modeling (Beza et al., 2023; Hagos et al., 2022).

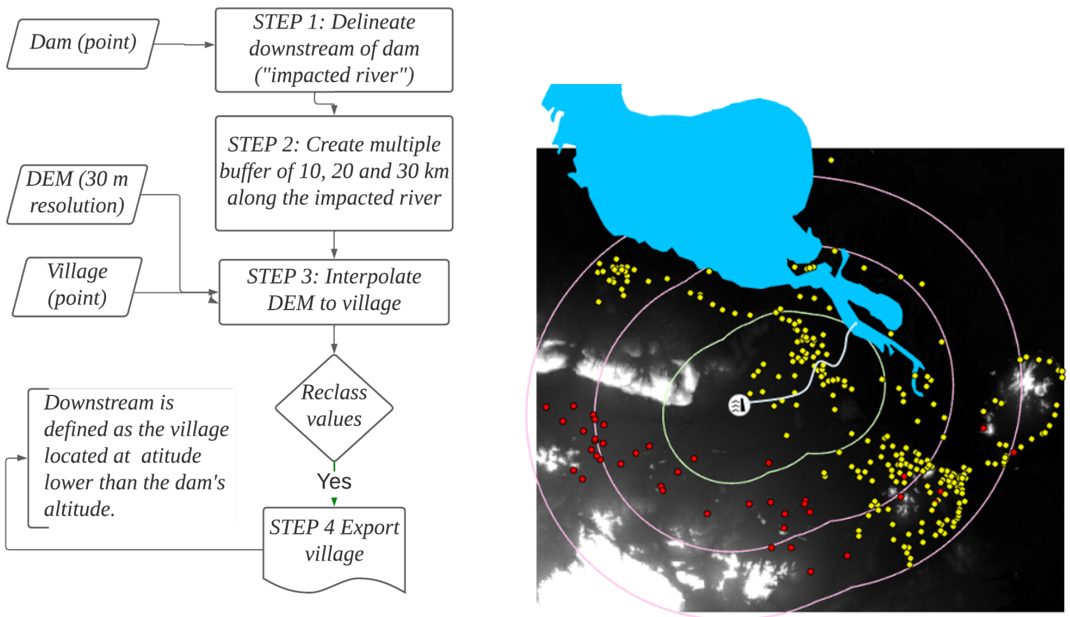


Figure 3: Flow diagram showing the steps taken for study population selection

To comprehensively understand the full extent of dam impacts, we created three buffer zones (referred as potential impact zones) around delineated impacted river segments (from step 1). These zones were set at 10 km, 20 km, and extended up to 30 km from the impacted river segments, as outlined in step 3, allowing identification of all villages falling within each zone. To add a vertical dimension, we utilized the SRTM 30m resolution digital elevation model to assign elevation values to each identified village (step 4). We then compared these elevations to the respective dam elevations, classifying villages as either above or below the dam's height, selecting those villages at elevations lower than the dam, as the downstream area of influence (step 4). In total we sampled 433 and 50 villages from 2013 and 2019 respectively within 30 Km from the impacted river segment for analysis (Table 3).

Table 3: Sample size

Dam	Altitude (masl)	Type	Sample village 2013	Sample village 2019
Ajhang	35	Irrigation	255	26
Battambang	51	MPD	143	17
Lower Sesan 2	59	HP	35	7
Total			433	50

1.2.3 Variable description

a. Dependent variable

We developed 5 indices that capture communities' accessibility to natural, physical, social, financial and human resources respectively, selecting 22 variables as proxy measures to develop these indices (Table 4) following the process listed in Figure 4.

The process of selecting the 22 proxy variables involved several stages starting with initial identification of potential measures from a review of twenty peer reviewed articles. We reviewed studies focused on agrarian livelihoods and adaptation within South and Southeast Asia. Drawing on the SLF, which emphasizes access to natural, financial, human, physical, and social capitals for sustainable livelihood practices, we identified key factors—both barriers and motivators—related to adaptation decisions and adaptive capacity.

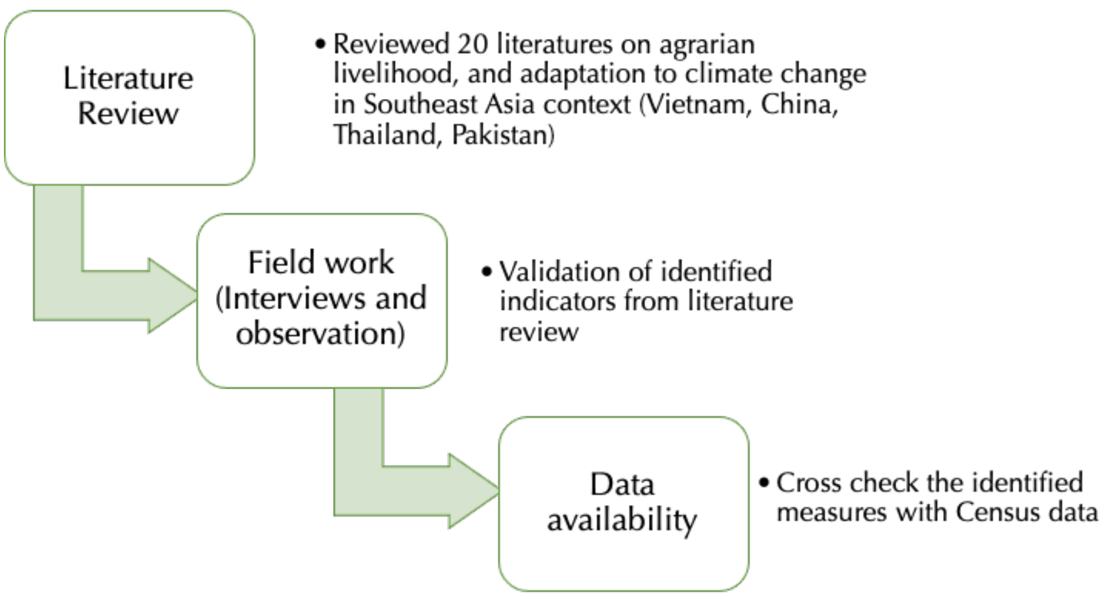


Figure 4: Flow chart showing the process of variable identification

Focusing on this region allows for a context-specific exploration of how farmers adjust their resource accessibility and livelihood strategies in response to environmental change, such as those driven by dam construction. After reviewing the literature, we validated the identified measures using field information collected in 2022 through informal interviews and observations. Finally, we cross-checked these measures against available data from the Cambodia Agricultural Census of 2013 and 2019, finalizing the list of variables for analysis.

Table 4: List of variables used for building indices

Indices	Measures	Indicator	Unit[2]	Questions[1]	Source
Natural	Access to land for various livelihood activities	N_1: Engagement in cultivation	Proportion	Did you or any of your household members engage in any crop cultivation activity during the last 12 months?	(Bui & Do, 2021; Kasem & Thapa, 2011; N. A. Khan et al., 2021; Yang et al., 2020; C. Zhang et al., 2020)
		N_2: Ownership of land	Proportion	What is the land tenure?	
		N_3: Parcel for livestock	Proportion	land use of the parcel for livestock in the last 12 months	
		N_4: Parcel for aquaculture	Proportion	land use of the parcel for aquaculture in the last 12 months	
		N_5: Parcel for forest/wooded land	Proportion	Do you have any forest and other wooded lands that are part of this agricultural holding as of this day?	
	Access to water	N_6: Engagement in fish catching	Proportion	Did your household engage in any own-account fishing activity (any catching of fish and aquatic products) in the inland or marine water during the last 12 months?	
	Access to forest	N_7: Engagement in forestry	Proportion	Did your household engage in any own-account forestry-related activities in the last 12 months?	

Table 4 (cont'd)

Human	Access to laborers	H_1: Total household members available for economic activities	Mean number	Total Number of Members as of day of visit	(Abid *et al.*, 2016; Shrestha, Chaweewan and Arunyawat, 2017; Salaisook, Faysse and Tsusaka, 2020; Jin *et al.*, 2021; Khan *et al.*, 2021; Vo, Mizunoya and Nguyen, 2021)
	Access to education	H_2: HH head with formal education	Proportion		
	Access to knowledge and skills	H_3: Age of HH head	Years	What is the age of HH head?	
		H_4: Access to agricultural information	Proportion	Did you receive or access any agricultural information that helped you manage the agricultural holding during the last 12 months?	
Financial	Wealth	F_1: TLU	Mean TLU[3]		(Jin et al., 2016; N. A. Khan et al., 2021; Naqvi et al., 2020; N. T. T. Pham et al., 2019; Salaisook et al., 2020; Vo et al., 2021)
	Access to credit	F_2: Access to credit/loan for agricultural purpose	Proportion	Did you avail the credit/loan during the last 12 months for agricultural purpose?	
	Access to banking facilities	F_3: Household using bank	Proportion	Did you avail the credit/loan during the last 12 months? Bank	
	Access to microfinance	F_4: Household using Microfinance for credit	Proportion	Did you avail the credit/loan during the last 12 months from these sources? Microfinance	

Table 4 (cont'd)

Physical	Access to irrigation facilities	P_1: Household with irrigation facilities	Proportion	Did you or your household use irrigation in this holding during the last 12 months?	(Jin et al., 2021; N. A. Khan et al., 2021; N. T. T. Pham et al., 2019; Yang et al., 2020)
	Access to market	P_2: Household using market either for sale or for information	Proportion	Did you bring and sell your agricultural produce/products in this nearest market from your holding/house during the last 12 months?	
	Access to school	P_3: Household with members attending school	Proportion	Household members' currently attending school?	
Social	Access to informal networks for credit	S_1: Relatives/friends	Proportion	Did you avail the credit/loan during the last 12 months from these sources?	(Bui & Do, 2021; Jin et al., 2021; Kasem & Thapa, 2011; I. Khan et al., 2020; N. T. T. Pham et al., 2019)
		S_2: money lender	Proportion		
	Access to network for agricultural information	S_3: Main source of agricultural information-farmers	Proportion	where did you receive or access the agricultural information?	
		S_4: Main source of agricultural information-Government	Proportion		

Table 4 (cont'd)

Note:

1. *These are the questions used to collect information in the Census of Agriculture in Cambodia 2013 and Inter-Censal 2019 at household level.*
2. *The dataset was initially recorded at the household level. To conduct community-level analysis, further data processing was performed in R using `dplyr` package, where household-level variables were aggregated to the community level using appropriate summary statistics (e.g., means, proportions) depending on the nature of the variable.*
3. *Total Livestock Unit: TLU represents the weighted sum of domestic animals owned. TLU is a standardized metric of total livestock owned using a weighted value for each livelihood species as provided by FAO (2005) in the Cambodian context: 0.65 for cattle, 0.7 for buffalo, 0.1 for sheep and goats, 0.25 for pigs, and 0.01 for chickens/poultry.*

We applied principle component analysis (PCA) to build indices representing access to the five livelihood capitals for both years 2013 and 2019. PCA is a widely used data reduction technique that identifies patterns in large datasets (Tareq et al., 2021) and is commonly used for developing capital indices (Y. He & Ahmed, 2022; Xu et al., 2023). This method was applied to the selected proxy variables for each capital (Table 4), with the first principal component for each livelihood capital used to create the indices, representing the most significant underlying structure of the data.

b. Independent variables

Dam effect (X_1) To capture the temporal changes between the pre- and post-dam construction periods, we created the dummy variable *Year* (1 = 2019, 0 = 2013). This variable serves as a key indicator for the shifts in resource accessibility that can be attributed to the dam over time (H1).

Spatial-temporal effect (X_2) To assess the spatial variation in the dam's impact, we developed two interaction terms, each capturing the interaction between time (pre- and post-dam) and the impact zones (Zones 1 and 2), with Zone 3 as the reference for comparison. These interaction terms evaluate how the dam's effects differ across spatial zones (H2).

Additionally, we explored dam effects by its type (X_3) (e.g., hydropower, multi-purpose and irrigation). We controlled for other contextual factors including nightlight effect using Night Time Lights data at 2014 and 2019 (Elvidge et al., 2021; *VIIRS Nighttime Light (VNL)*, 2021), which serves as the proxy for socio-economic and infrastructural development (Bargain et al., 2023; Quan et al., 2023; Kocornik-Mina et al., 2020; Singhal et al., 2020) that can influence resource accessibility (Fan et al., 2022).

1.2.4 Analytical approach

We employed a multi-step analysis, beginning with testing differences in resource accessibility before and after dam construction using a combination of non-parametric tests, followed by employing a mixed effect model to test our hypotheses. Finally, we also included an analysis for both balanced and unbalanced data to ensure robustness and accuracy in the findings.

Preliminary tests Given the non-normality of the data, we first applied non-parametric tests, including Mann-Whitney tests at 95 % confidence intervals for proxy measures of each index (Calvi et al., 2020). Then, we conducted independent t-tests to determine the direction of change with significance level. After developing indices representing different livelihood capitals, we performed Wilcoxon Signed-Rank Test (matched), to each of the indices to evaluate significant differences in resource access pre- and post-dam periods (Abbott et al., 2022).

Mixed-Effects Model We employed mixed-effects, unbalanced panel data analysis to assess the effects of the dam. To evaluate the effects on each type of livelihood resource, we developed candidate sets of linear mixed effects models, two models (random and fixed effect) corresponding to each of the five livelihood resources (using the *plm* package in R) (Figure 5). Given non-normal data distribution of indices value (based on Shapiro-Wilk test using an α level of 0.05), we used log-transformed values for each index value in the model.

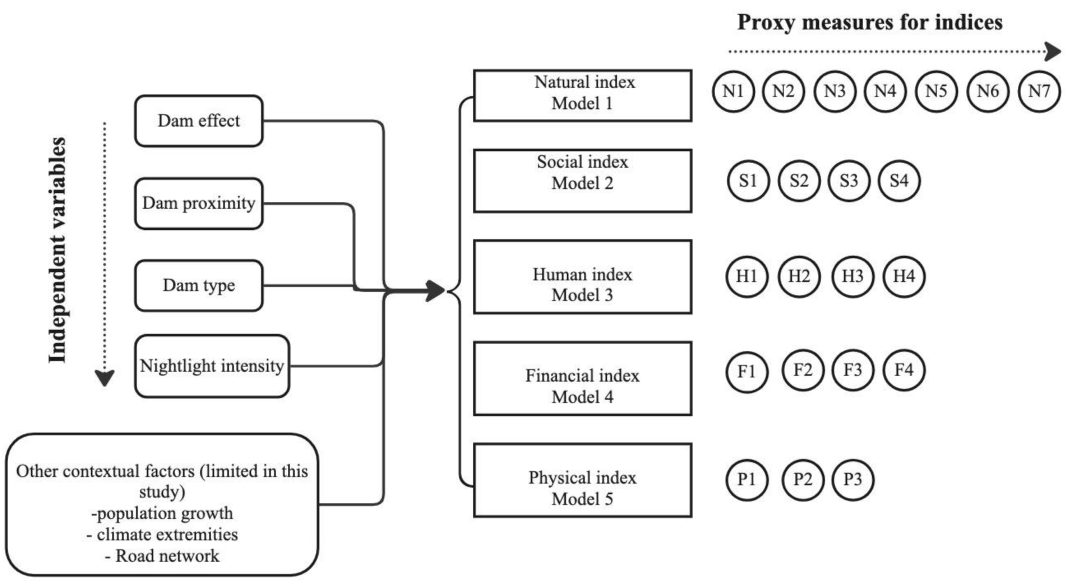


Figure 5: Models specific to each resource access

We applied a random effects model for all five indices considering several factors. First, the random effects approach accounts for unobserved heterogeneity between villages, capturing village-specific effects that may not change over time but still influence resource accessibility. Second, the model allows for time-invariant variables, such as the impact zone (proximity to the dam) and dam type, to remain in the analysis, providing estimates for their coefficients. This is important as it offers insights into how dam proximity and dam function type affect resource access over time. Additionally, the random effects model provides an average effect for each village, giving us a broader view of the dam's impacts while controlling for both observed and unobserved factors. This approach also ensures that village-level variations and other factors that do not change over time are accounted for, making the model robust.

Robustness of the estimates To ensure the robustness of estimates, we ran random effects models with the full sample (unbalanced panel data, N= 433) and common sample (balanced panel data, N=50). We checked any inconsistencies in the results based on effect size (coefficient value) and direction of association, standard error value and confidence level. In case of difference in effect size, we reported the coefficient value with small standard errors and high confidence levels. We reported estimates using percentage changes, derived from the exponentiation of β.

1.3 Results

1.3.1 Findings of preliminary tests

Non-parametric Mann-Whitney tests and independent t-tests revealed significant changes in resource access for several proxy measures across all livelihood capitals before and after the post-dam periods. Specifically, 18 out of 22 measures showed significant differences at the 95% confidence level ($p < 0.05$) over time. Notably, social, physical, and financial resource access measures exhibited moderate to large effect sizes (Cohen's d ≥ 0.5) (see APPENDIX A Table 10). For instance, access to bank services (Cohen's d = 1.38) and credit (Cohen's d = 0.80), as well as access to informal networks—such as friends (Cohen's d = 1.38) and money lenders (Cohen's d = 0.91)—demonstrated significant shifts. Additionally, access to information from government sources exhibited a particularly pronounced change (Cohen's d = 1.92), indicating substantial alterations in resource access across these categories.

The Wilcoxon Signed-Rank Test further validated these results, showing notable differences in all indices over time, with the exception of human capital ($p > 0.05$), as illustrated in Table 5.

Table 5: Summary of proxy indicators for each index and distribution of the indices value, representing access to different livelihood resource, before and after dam construction across 50 matched sampled downstream communities

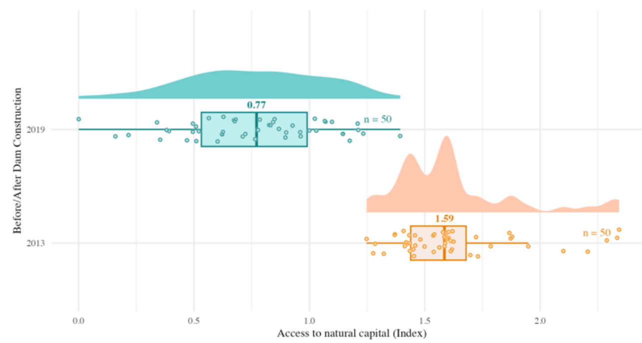
Indices	Indicator	2013 Mean (SD)	2019 Mean (SD)	Distribution of indices showing median value (Green color indicates 2019 and orange indicates 2013)
Natural	N_1: Engagement in cultivation	0.841 (0.233)	0.9 (0.01)	
	N_2: Ownership of land	0.972 (0.049)	0.971 (0.053)	
	N_3: Parcel for livestock	0.696 (0.260)	0.632 (0.171)	
	N_4: Parcel for aquaculture	0.001 (0.017)	0.788 (0.306)	
	N_5: Parcel for forest/wooded land	0.129 (0.243)	0.048 (0.068)	
	N_6: Engagement in fish catching	0.265 (0.306)	0.247 (0.298)	
	N_7: Engagement in forestry	0.002 (0.014)	0.869 (0.196)	

Table 5 (cont'd)

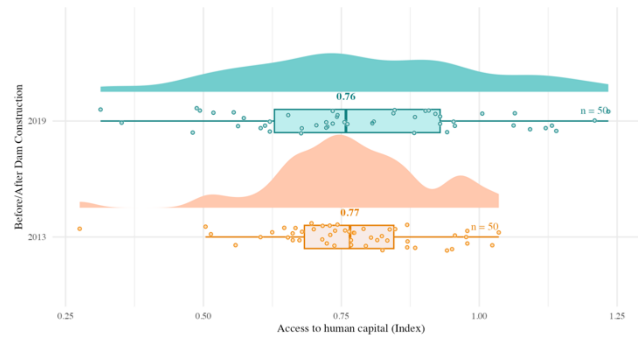
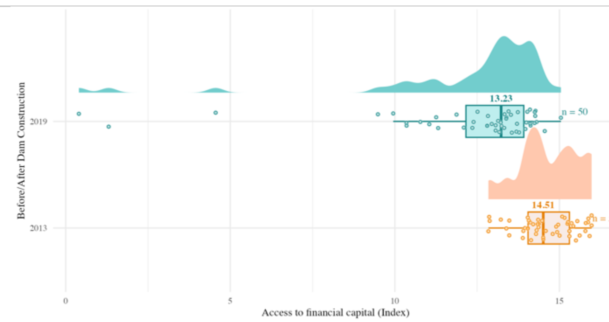
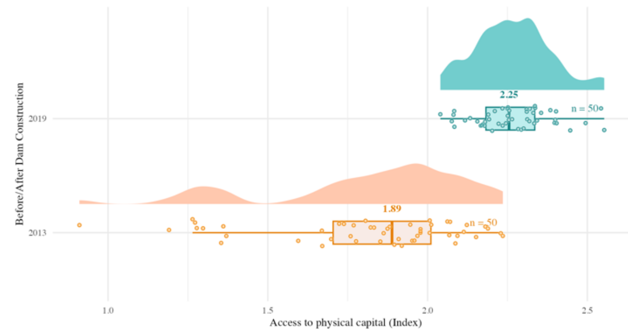
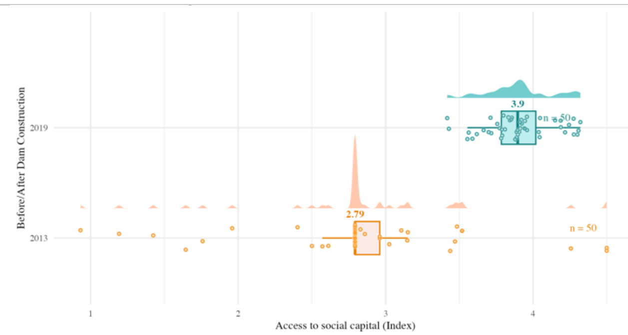
Human	H_1: Total household members available for economic activities	4.652 (0.654)	4.19 (0.52)	
	H_2: HH head with formal education	0.902 (0.169)	0.805 (0.110)	
	H_3: Age of HH head	48.598 (4.961)	46.737 (3.374)	
	H_4: Access to agricultural information	0.357 (0.114)	0.361 (0.155)	
Financial	F_1: TLU	1.5 (1.06)	5.664 (16.035)	
	F_2: Access to credit/loan for agricultural purpose	0.175 (0.065)	0.474 (0.165)	
	F_3: Household using bank	0.147 (0.203)	0.329 (0.248)	
	F_4: Household using Microfinance for credit	0.488 (0.292)	0.525 (0.245)	

Table 5 (cont'd)

Physical	P_1: Household with irrigation facilities	0.243 (0.329)	0.32 (0.133)	
	P_2: Household using market either for sale or for information	0.218 (0.051)	0.006 (0.022)	
	P_3: Household with members attending school	1.132 (0.300)	0.195 (0.110)	
Social	S_1: Main source of credit-Relatives/friends	0.253 (0.248)	0.01 (0.027)	
	S_2: Main source of credit-money lender	0.201 (0.226)	0.047 (0.083)	
	S_3: Main source of agricultural information-farmers	0.306 (0.310)	0.263 (0.174)	
	S_4: Main source of agricultural information-Government	0.573 (0.334)	0.099 (0.102)	

These preliminary findings highlight the nuanced impact of temporal changes on different aspects of resource access. However, to understand these shifts in relation to dams, we further explored the causal relationships in the subsequent mixed-effects model discussed in the following section.

1.3.2 Findings of mixed effect model

The random effects models using the unbalanced panel data explained a substantial portion of the variance in access to livelihood resources, with adjusted R^2 values exceeding 0.61 for all resources except financial (APPENDIX B Table 11). In contrast, when using balanced panel data, R^2 values decreased to below 0.20 for most resources, except for natural resources ((APPENDIX B Table 12). This reduction is primarily due to the smaller sample size and reduced variability in the balanced dataset.

We reported results from both balanced and unbalanced panels for comparison (APPENDIX B Table 11 and Table 12); however, we focus on the unbalanced panel estimates (

Figure *6*) due to its larger sample size, which provides more precise estimates with lower standard errors. The consistency of coefficient estimates across both panels indicates that our findings are robust. Nonetheless, the increased statistical power in the unbalanced panel allows for more reliable detection of statistically significant effects.

Post-dam effect on resource access:

The models revealed significant impacts of dams on downstream communities' access to diverse livelihood resources, mainly natural, financial and physical with varying directions of effect. Access to natural resources decreased by 36% ($\beta = -0.44$, SE = 0.06, $p < 0.001$) and financial resources by 32% ($\beta = -0.38$, SE = 0.06, $p < 0.001$) compared to the pre-dam period (2013). Conversely, access to physical resources increased by 31% ($\beta = 0.27$, SE = 0.04, $p < 0.001$).

Spatial-temporal changes in resource accessibility

We observed significant spatial variation in resource access, particularly for natural and social capitals, across communities located at different impact zones. Communities within 10 kilometers from the dam-impacted river segment (Zone 1) showed 2% less access to natural resources ($\beta = -0.09$, SE = 0.03, $p < 0.01$) compared to the communities located beyond 20 kilometers (Zone 3). Communities situated between 10 to 20 kilometers from the dam-impacted river segment (zone 2) demonstrated 8% less access to social resources ($\beta = -0.08$, SE = 0.04, $p < 0.05$).

We did not observe any variation in resource access among communities closer to the dam post-dam construction (impact zones 1 and 2), except for financial resources, when compared during the pre-dam period. The estimates indicate an increase in access to financial resources for communities located within 10 kilometers of the dam-affected river segment (impact zone 1), by approximately 35% ($\beta = 0.3$, SE = 0.08, $p < 0.001$). Similarly, communities situated between 10 to 20 kilometers from the dam-impacted river segment (zone 2) experienced a 34% increase ($\beta = 0.29$, SE = 0.09, $p < 0.001$) compared to the pre-dam period.

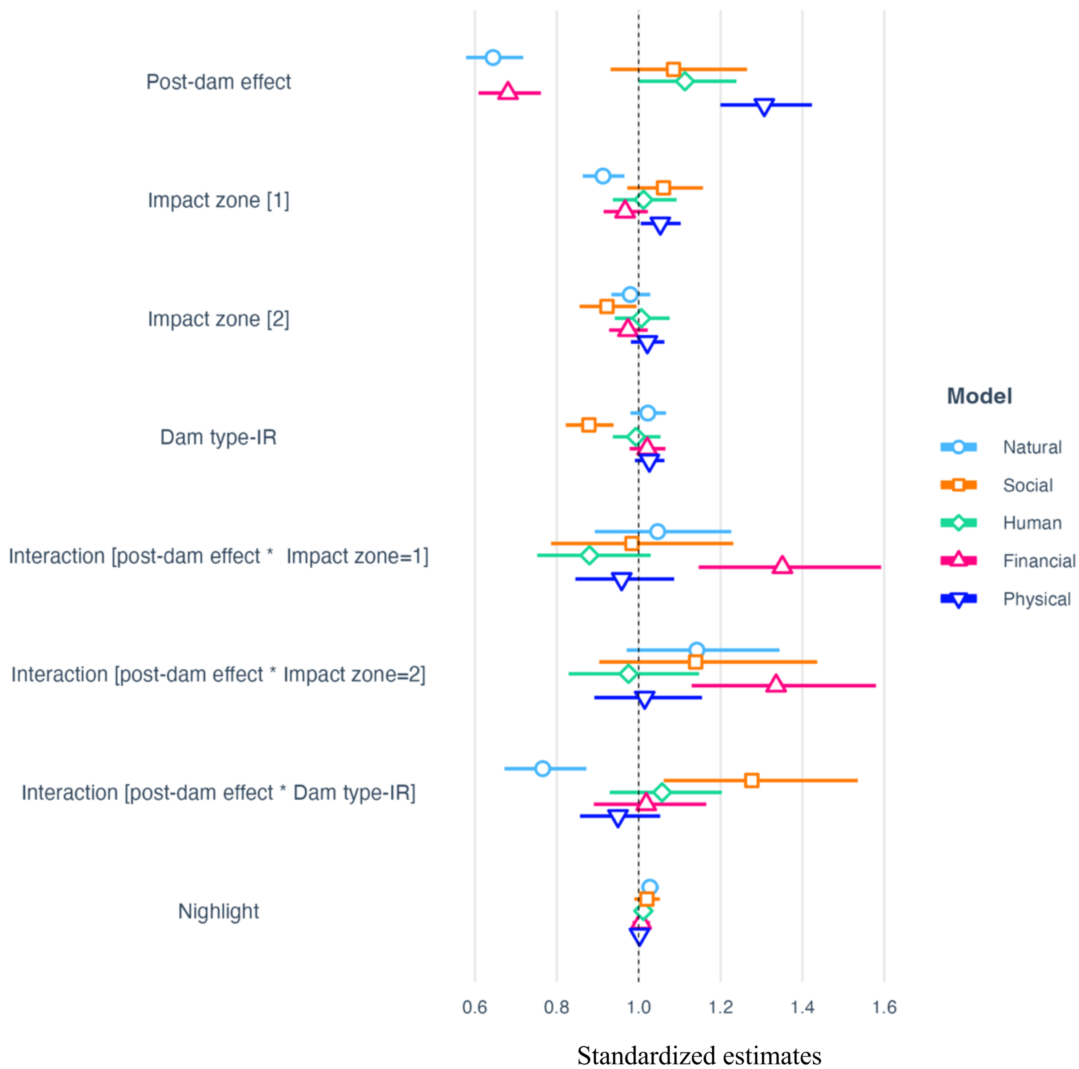


Figure 6: Results from mixed effect models

Dam type and variation in resource access:

When comparing variation in resource access among communities across different dam types, we found a significant 12% decrease in access to social resources for communities located near the Ajhang Irrigation Dam ($\beta = -0.13$, SE = 0.03, $p < 0.001$), compared to those near the Battambang and Lower Sesan 2 dams. However, after dam construction, we found increase in access to social resources in these communities ($\beta = 0.24$, SE = 0.09, $p < 0.01$) compared to the pre-dam period. In contrast, we observed decrease in access to natural resources by 24% ($\beta = -0.27$, SE = 0.07, $p < 0.001$) post-dam construction. We did not find any significant changes for physical, financial, or human resources based on dam types.

1.4 Discussion

This study reveals the complex and multifaceted impacts of dams on downstream communities' access to different livelihood resources including natural, financial, physical and social. The findings highlight that the impact of dams varied by dam type and that these impacts extend beyond the immediate proximity of the dam structure (i.e. beyond 10 km), contributing to the growing body of literature on the social impacts of dams.

1.4.1 Spatial-temporal changes in resource accessibility

Natural resource

The most prominent changes observed post-dam construction are a significant decrease in access to natural resources, which aligns with global studies on the impacts of hydropower dams (Arthur et al., 2020; Castro-Diaz et al., 2023; Fan et al., 2022; Nhung, 2017a). Furthermore, our findings reveal spatial variation in natural resource access across communities located in different impact zones. Specifically, communities located closer to dams (<10 km) experience more pronounced negative effects compared to those farther away (>20 km). This pattern corresponds with existing studies that highlight how the effects of dams, on greenness (Fan et al., 2022), changes in forestland, grassland and cultivation land (Lin & Qi, 2019; Zhao et al., 2013), and alterations in water and sediment flow (Richter et al., 2010), are often concentrated in areas nearest to the dam.

This reduction in natural resource access is critical, especially in rural communities with predominantly natural resource-based livelihoods (Y. He & Ahmed, 2022). Scholars have reported negative effects on common-pool resources like rivers, forests, and pastureland, leading to water scarcity, degraded soil quality and reduced fish production—factors that directly affect locals' primary livelihoods, such as cultivation and fishing (Arthur et al., 2020; Owusu et al., 2019). These observations are in accord with our findings, where we found a decrease in the proportion of households using land parcels for livestock and forest-based activities, and fishing, with a corresponding increase in aquaculture and crop cultivation (see APPENDIX A Table 10). This shift indicates not only a change in land-use patterns but also a direct response to reduced access to natural resources such as forest products and fish.

While communities continue to access forest resources, the sharp decline in fishing activities underscores the broader environmental changes that have followed dam construction. This mirrors findings from other studies in the LMR where fisheries have suffered due to altered hydrological regimes, impacting both fish populations and community livelihoods (Soukhaphon et al., 2021). The increased reliance on alternative livelihood activities, such as aquaculture, intensified land use, and heightened dependence on forest resources, suggests that communities are adapting to the changing availability of natural resources (Piesse, 2016; Robert, 2017). Similar shifts in local livelihoods post dam construction are reported, for example, after construction of the Kamchay Dam in Cambodia (Siciliano et al., 2015) and the Ghana's Bui dam in Ghana (Owusu et al., 2019).

Financial resource

The significant decrease in communities' access to financial resources post dam construction suggests that dams can negatively impact local economies, especially those that rely heavily on natural resources. The study suggest that natural capital serves as the foundation for securing other resources, including financial, particularly in natural resource-dependent livelihoods such as fishing and farming (Xu et al., 2023). However, when observing the spatial changes in financial resource access over time among downstream communities at different impact zones, our findings reveal an increase in financial resource access for those located within 10 Km (zone 1) and between 10-20 Km of the dam impacted river segment.

This contrasting trend suggests that while there is an overall reduction in financial access post-dam construction (for communities within 30 km), certain communities closer to the dam may experience unique opportunities that improve their financial access. Castro-Diaz *et al.* (2023) also identified both positive and negative effects of hydropower dams on financial resources, suggesting that these impacts can be context-specific.

The increase in financial access in impact zones 1 and 2 could be attributed to economic activities such as agricultural intensification and aquaculture, which are likely facilitated by improved access to irrigation infrastructure, banking services, microfinance, and credit (Arthur *et al.*, 2020; Green, 2020; see APPENDIX A Table 10). However, it is important to mention that this financial benefit may be limited to only a few communities (Fung et al., 2019) within these zones that are better positioned to leverage new opportunities arising from infrastructural changes, a factor not explored in this study.

Furthermore, unlike the decrease in natural resource access, which is concentrated in areas closer to the dam, the effects on financial resources appear to extend beyond the 10 km radius. This suggests that the economic impacts of dam construction may persist and spread over time, affecting wider geographical area (Goodman, 2024).

Physical resource

Not surprisingly, there is an increase in access to physical resources after dam construction, which is consistent with most studies that show how dams often bring improved physical infrastructure such as roads, energy access, schools, health, markets, and irrigation systems to nearby communities (Beck et al., 2012b; Castro-Diaz et al., 2023; Hensengerth, 2018). However, there is disproportionality in resource access as our estimates suggest greater physical resource access in communities closer to the dam (Zone 1). This finding aligns with studies suggesting that communities in proximity to infrastructural projects often receive the greatest benefits. For example, Aung, Guido and Stijn (2017) observed differential benefits of the Swar Dam project among paddy farmers in the south-central part of Myanmar due to unfair and untimely distribution of the irrigation water by the irrigation department. They found 50 percent of head and middle end-users experienced sufficient water availability while tail end-uses reported water shortages.

Social resource

We found a significant effect on access to social resources post- dam construction among downstream communities located within 10-20 km of affected river segments (zone 2), suggesting potential disruptions to their social networks. This concern was raised by Tilt, Braun and He (2009) in their review of dam-induced displacement and resettlement.

Existing studies on changes in social capital, though limited, primarily focus on cognitive aspects such as conflict, loss of traditional ceremonies, and participation (Castro-Diaz et al., 2023; Fung et al., 2019). Structural aspects, like relations with neighbors, church attendance, and having relatives in the city, have received less attention (Arthur et al., 2020; Mayer et al., 2022).These studies, mostly centered on resettled and host communities, consistently report negative effects of both large and small dams on social resources. For instance, Arthur *et al.* (2020) found that communities perceived adverse effects of the Bui Dam on their informal ties and community connections.

While there is a lack of research capturing the spatial variation in access to social resources, some scholars suggest delayed and indirect impacts of dams on social aspects for communities farther downstream (Richter et al., 2010). Zone 2 communities might experience these delayed effects more acutely as they adapt to gradual changes in their environment and livelihoods. These impacts can be related to the observed decrease in natural resources in Zone 2 and potential changes in livelihoods, which may lead to a breakdown of traditional social structures and support systems, for example a decrease in availability of relatives/friends and money lenders for credit and agricultural information on average for sampled communities in general (see APPENDIX A Table 10).

Human resource

The study did not find significant spatial and temporal changes in access to human resources post-dam construction. However, when examining specific measures such as access to household labor for livelihood activities, a significant decrease over time was observed, aligning with findings from previous research. For instance Calvi *et al.* (2020) reported a decrease in family labor due to outmigration after the Belo Monte dam construction in the Brazilian Amazon. Similarly, Owusu *et al.* (2019) observed outmigration among low-income groups due to disproportionate distribution of amenities like electricity and improved water supply following Ghana's Bui dam hydroelectricity project.

Further studies require considering a broader range of human resource measures. We also recommend exploring migration patterns and their relationships to dam construction.

1.4.2 Dam Type and Resource Access

The varying impacts of different dam types on resource access contribute to a nuanced understanding of dam effects. Interestingly, despite an overall decrease in social resource accessibility among sampled communities, we found a 27% increase in access to social resources among communities downstream of the Ajhang Irrigation Dam, compared to those near hydropower and multi-purpose dams. This occurs despite these communities experiencing a slight 2% average decrease in natural resource access. This finding suggests complex social dynamics that may be associated with factors such as increased crop cultivation at the expense of fishing or forest parcels, increased interaction among farmers, and community cooperation due to shared irrigation infrastructure. These results align with Dillon's (2011) study in Mali, which found that small-scale irrigation projects led to increased agricultural production and informal food sharing through collective management practices.

The contrasting effects of different dam types highlight the need for context-specific assessments. For instance, Kirchherr, Pohlner and Charles (2016) emphasized that the socio-economic impacts of dams vary significantly based on their purpose, size, and local context.

1.4.3 Policy implications

This study contributes to a more nuanced understanding of dam impacts, exploring the differential impact of dams on diverse livelihood resources across downstream communities at different dam proximity. This granularity is often underrepresented in existing studies on the social impacts of dam construction. Our findings provide insights for improving Environmental Impact Assessments (EIAs) associated with dam construction and enhancing adaptation programs, particularly in regions affected by dam construction.

Comprehensive, Resource-Specific Assessments

The findings on differential impacts across various livelihood capitals (natural, social, physical, and financial) emphasize the need for EIAs to extend the range of resource categories beyond natural and economic. This would ensure that all facets of community livelihoods are protected and supported. Adaptation programs should also be designed with a multi-dimensional approach, targeting the diverse ways communities use diverse resources instead of limiting to natural resources.

Incorporating Spatial Differentiation in EIAs

The study's identification of distinct zones of impact for diverse resources suggests that future EIAs should move beyond broad, one-size-fits-all approaches. Policy should consider spatial differentiation, ensuring that assessments consider varying effects based on different proximity to dam-impacted rivers and other contextual factors. This would provide more localized data on environmental and social impacts, allowing for tailored mitigation strategies. Such differentiated EIAs would improve accuracy in identifying affected downstream communities and resources, guiding fair compensation mechanisms and targeted interventions to mitigate negative impacts and enhance positive outcomes of dam construction.

Long-term Monitoring and Temporal Dynamics

Current assessments often focus on short-term impacts, but the temporal dynamics observed in this research indicate the need for ongoing evaluations to fully understand the evolving effects of dams on downstream communities. By institutionalizing long-term monitoring, policymakers can ensure that adaptation measures remain responsive and effective over time.

1.4.4 Limitations and Future Research

While our study provides valuable insights into the impacts of dams on livelihood resources, it is important to acknowledge several limitations and propose directions for future research:

1. Unbalanced panel data: We reported estimates from unbalanced panel data. Although the samples were drawn from the same population in both 2013 (488 observations) and 2019 (50 observations), the significant difference in sample sizes raises potential concerns about nonrandom missingness. The smaller sample size in 2019 may introduce bias if certain characteristics are underrepresented. Future research should aim to achieve more balanced sampling across time periods to reduce potential biases and ensure more robust comparisons.
2. Limited sample of dam types: This study includes only three dams, each of a different type. This limited sample may not fully capture the differential impacts across various dam types. Future research should incorporate a larger number and diversity of dams to provide a more comprehensive understanding of type-specific impacts.
3. Limited measures of livelihood resources: Due to data constraints, we used a limited set of measures to construct our resource indices. Future studies should incorporate additional measures such as household energy access, health effects, labor movement, cognitive aspects of social capital (e.g., trust, norms, and shared values). These additions would provide a more nuanced understanding of changes in physical, human and social resources, facilitating better comparisons with existing literature.
4. Need for qualitative research: Our quantitative findings could be complemented by qualitative research exploring the lived experiences of affected communities. In-depth

interviews and focus group discussions could provide rich contextual information and help explain some of the quantitative patterns observed.

5. Contextual factors: While we used nightlight intensity as a comprehensive measure of socio-economic conditions, future studies could control for additional contextual factors such as population growth, climate extremities and trends, government policies and interventions.

CHAPTER II: HOW DO HOUSEHOLDS ASSESS DROUGHT RISK: INSIGHTS FROM IRRIGATED AND FLOOD-PULSE COMMUNITIES, CAMBODIA

2.1 Introduction

The Lower Mekong Region (LMR), including the connected Tonle Sap Lake and its downstream floodplain communities, faces increasing risk to climate change. According to the International Panel on Climate Change (IPCC, 2014), key risks are characterized by high-frequency climate-related hazards, minimal capacity to adapt, and persistent socio-economic vulnerabilities such as poverty (Oppenheimer et al., 2014). These criteria are highly relevant to the LMR where rapid hydrological, ecological, and socio-economic changes are occurring due to dam construction, industrial farming, and forest plantations (Pokharel et al., 2018; Spruce et al., 2020).

These developments have increased the vulnerability of ecosystems and dependent livelihoods as well as exacerbating conflict, inequality, economic stresses, and poverty (Baird & Barney, 2017; Beban et al., 2017; Sok & Yu, 2015). Such vulnerable systems and communities are highly susceptible to climate change (Oppenheimer et al., 2014). Of particular concern is the increasing frequency, duration, and severity of droughts over the past two decades, with notable drought events in 2004-2005, 2009-2010, 2016, (Adamson & Bird, 2010; MRC, 2019a) and 2019-2020 (Keovilignavong et al., 2023). Climate projections suggest that rising temperatures, prolonged dry spells, and lower river flows will worsen drought conditions over the next 30 to 90 years, threatening the livelihoods of 70-80 percent of the region's subsistence farmers and fishers (MRC, 2019).

While dams and irrigation infrastructures are intended to mitigate drought risks, irregular water distribution, especially during wet and dry seasons, and the absence of benefit-sharing mechanisms have worsened water scarcity (Nhung, 2017). This has disproportionately affected downstream countries like Cambodia leading to increased crop losses (Yamsiri, 2014), reduced fish yields due to altered water and nutrient flows (Yoshida et al., 2020), and water conflicts within communities (Aung et al., 2017).

The populations affected by these changes are likely to perceive high drought risks to their farms and livelihoods, particularly under resource constraints. This perception can influence their responses such as sand mining, exploiting groundwater and land resources (Piesse, 2016; Robert,

2017) as well as their acceptance of climate change adaptation measures (Bastakoti et al., 2014; Dang et al., 2014). Some behaviors can worsen drought conditions and exacerbate system vulnerabilities. Thus, it is crucial to understand local perceptions of drought risk, which is limitedly addressed in existing studies of risk perception in relation to climate change, dams and interconnected hydro-agricultural-fisheries system like the LMR.

2.1.1 Risk perception studies

Studies of risk perception gained prominence in the 1970s and 1980s when scholars in psychology, for example, Paul Solvic and Daniel Kahneman, identified inconsistencies between the scientific community's and the public's understanding of risk and its influence on decision-making. Initially, the focus was on technological hazards such as nuclear power risks (Slovic, 1987). However, the need to understand individuals' perceptions of risk has since been widely adopted in behavioral science and climate change studies, where false perceptions of lower risk and high security with existing practices can exacerbate vulnerability if individuals fail to adapt (Cardona et al., 2012).

A large body of research explores how people perceive risks related to natural hazards such as floods (Botzen et al., 2009; Kellens et al., 2013; Siegrist & Árvai, 2020). Yet, empirical studies assessing perceived drought risk at the household level are limited, and most are concentrated in developed countries such as Spain (Urquijo & De Stefano, 2016) and the Netherlands (Duinen et al., 2015). In the Global South, some studies have examined farmers' perceptions of climate change risks more broadly as seen in Vietnam (Dang et al., 2014) and China (Tang et al., 2013a). These studies, however, tend to approach risk perception from a unidimensional perspective, focusing a limited number of characteristics of such hazards—either the probability of future water scarcity or the severity of its consequences on livelihoods.

Research grounded in the psychometric paradigm argues that feelings of dread or affect are primary determinants of public perception and acceptance of risk (Slovic et al., 2012; Tang et al., 2013). This is particularly relevant for hazards like drought which are characterized by their indistinct and uncontrollable nature, and uneven, delayed impacts (Slovic, 2016). Such arguments suggest the need to adopt a more comprehensive approach to risk assessment, incorporating the multi-characteristics of hazards—such as the perceived probability of occurrence, severity of consequences, and emotional responses like fear or worry (Walpole & Wilson, 2021; Wilson et al., 2019).

Considerable research has explored the individual correlates that shape risk perception such as socio-economic, demographic, and psychosociological factors, which account for variation at the individual level. However, studies that integrate both individual factors and broader contextual elements—particularly those addressing variability at the community level—are limited, providing limited understanding of drought risk. To address this gap, we examined how households in irrigated and flood-pulse communities in Cambodia assess drought risk using a holistic approach. Specifically, we aimed to answer the following questions:

1. Do households' perceptions of drought risk vary within and across communities? If so,
2. What explains the heterogeneity in risk perception at the household level and by community type?

2.1.2 Drought and individual characteristics shaping risk perception

The notion of drought in tropical monsoon regions like LMR does not fit naturally with conventional perception, generally associated with consistently low and marginal rainfalls in the arid and semi-arid region, such as the Sahel in Africa or central Australia, where drought is more natural and permanent. Further, unlike other climatic hazards, for example floods, drought is a slow-onset phenomenon without a distinct end. It also stays longer and results in cumulative and broader impacts (Bachmair et al., 2016). Thus, drought severity and its impacts depend not only on its duration, intensity, spatial extent and site-specific characteristics (for example, soil properties, rainfall, hydrological flow), but also on socio-economic activities and the adaptive capacity of the social systems it affects (Adamson & Bird, 2010).

This unique context of drought in the LMR significantly influences how individuals perceive and respond to drought risks. The slow onset and gradual intensification of drought conditions can lead to delayed recognition of the problem, potentially resulting in inadequate preparedness among local populations. Moreover, the cumulative and wide-ranging impacts of drought in the region affects agriculture, fisheries, and water resources. As populations are repeatedly exposed to drought effects, their perceived risk is likely to be shaped by the interplay between evolving drought conditions and individual factors including situated contexts (Siegrist & Árvai, 2020). Therefore, our primary hypothesis is that households' risk perception is heterogenous, explained by bio-physical, experiential, socio-psychological, and geographical characteristics.

Biophysical Factors

Existing studies on flood and landslide risk perception have established a relationship between biophysical properties of the environment and risk perception, for example, the effects of elevation and proximity to water bodies (Botzen et al., 2009; Ho et al., 2008; Kellens et al., 2013). Due to the ambiguous nature of drought, risk is often shaped by exposure to the biophysical characteristics of the environment in which households are embedded. For example, living in areas without external water source creates resource constraints like water scarcity (Tang et al., 2013a; Urquijo & De Stefano, 2016). Thus, we hypothesize that

H1: Households located in the areas without an external water supply perceive greater drought risk compared to those with access to such a supply.

Experiential Factors

Direct experiences with stressors such as financial losses from drought are known to positively influence risk perception and precautionary behavior (Kellens et al., 2013; Tang et al., 2013; Wachinger et al., 2013). Thus, we expect that

H2: Households experiencing drought related financial damage in the past perceive greater risk today.

Socio-Psychological Factors

Planned behavioral theory suggests that individuals collect and process information as they interact with others, shaping their perceptions (Schlüter et al., 2017). Such ties are found to amplify direct experiences with risks (Wachinger et al., 2013). Households' social interactions can trigger memories of their past experiences of hazard that affected their livelihoods. Such discussions can evoke emotions and awareness that make risks feel more immediate and significant, ultimately heightening perception of risk (Tang et al., 2013a).Thus, we hypothesize that

H3: There is a positive relationship between household's social ties for information and their perception of drought risk.

Additionally, households' connections to various local institutions can provide diverse forms of support, such as credit, seeds, and training. This support can enhance households' adaptive capacity to manage risk (Adger, 2003; Cassidy & Barnes, 2012), potentially lowering perceived risk. Thus, we expect that

H4: Households' association to any community organizations lower their perceived risk of drought.

Studies have examined the importance of the psychological attributes of household in shaping risk perception. Perceived trust in authorities and confidence in protective measures can lower perceived risks as demonstrated by studies in Vietnam, China, and Spain (Tang et al., 2013a; Urquijo & De Stefano, 2016). Thus, we expect that

H5: Household's trust in existing water management boards/committees and infrastructures controlling drought risk can decrease drought risk perception.

Shi et al. (2016) found the positive relationship between the level of knowledge about the causes and consequences of climate change and public concern about climate change. Similarly, Botzen et al. (2009) reported that individuals with little knowledge about the causes of flood events lowered the perceptions of flood risk in Netherlands, also supported by other risk perception studies (Siegrist & Árvai, 2020). Thus, we expect that

H6: Households with little knowledge of the causes and consequences of drought ('subjective knowledge') have lower drought risk perceptions.

A household's perceived ability to manage drought impacts—shaped by their economic and personal resources—can significantly influence their perception of risk (Van Duinen et al., 2015). However, the relationship between perceived ability and risk perception may vary depending on the type of hazard. For instance, a study by Ho et al. (2008) in Taiwan found that while landslides typically affect small areas, affected households often adopt precautionary measures such as evacuation, which they perceive as effective for controlling outcomes, resulting in fewer casualties over time. In contrast, flood-affected households may remain in vulnerable areas and implement some precautionary measures, yet they often face persistent financial losses that diminish their perceived control. This reduction in perceived control can escalate their risk perception.

Drought, characterized by its widespread and long-term effects, presents a unique challenge compared to both landslides and floods and therefore its effect on perceived drought risk might vary depending on their circumstances.

While perceived ability has been linked to lower perceived risk, household wealth can moderate this relationship. Studies have shown that greater wealth is associated with lower perceived risk for financial investments. Additionally, perceptions of relative wealth, rather than absolute wealth, can influence an individual's willingness to engage in risky behavior (Fehr & Reichlin, 2021), thereby increasing their perceived ability (Slovic, 1987; Slovic & Weber, 2002), which in turn can lower their perceived risk. Thus, we hypothesize that

H7: The relationship between perceived ability and risk perception varies across different levels of wealth, with greater wealth enhancing perceived ability over drought risk

Geographical factors

Evidence suggests variability in risk perception across populations located at different geographical locations, for example, rural vs urban in Netherlands (Wachinger et al., 2013); communities with ground water vs surface water in Spain (Urquijo & De Stefano, 2016), flood prone urban communities with different population sizes in Pakistan (Rana et al., 2020). In our study, we examined the effect on perceived drought risk based on community location, those in proximity to irrigation canals and those in proximity to Tonle Sap Lake. We assume that households located closer to irrigation canals have better access to water for cultivation than those farther from the canals. Therefore, we hypothesize that

H8: Households in irrigated communities perceive a lower drought risk compared to households in flood-pulse communities.

Demographic factors

Risk perceptions vary across different demographic groups, necessitating the inclusion of age, education, and sex as explanatory variables. However, the direction of the association can vary depending on the study context or hazard type. For instance, studies have found negative effects of education on risk perception among populations facing multiple hazards in Pakistan and rural communities facing flood hazards in the Netherlands (Ali et al., 2022; Botzen et al., 2009). On the other hand, some studies have found the positive effects of education on risk perceptions among urban communities facing flood hazards in Pakistan (Rana et al., 2020). There are few studies reporting a negative relationship between age and risk perception (Botzen et al., 2009; Tang et al., 2013a). Similarly, very few studies have established a significant effect of gender on risk perception. For example, Dang et al. (2014) and Ho et al. (2008) have found a lower risk perception among males in Taiwan and Vietnam respectively. However, they did not find an effect of age and education on risk perception. These findings suggest no clear direction.

Thus, we did not set any hypotheses regarding associations between these factors and risk perception. However, we do include demographic characteristics as control variables.

2.1.3 Significance of this study

This study makes several significant contributions to the risk perception literature in the context of climate change, dams, and connected hydro-agricultural-fisheries systems like the LMR:

1. It adds to the limited literature on drought risk perception by examining various factors shaping household risk perceptions including biophysical, experiential, socio-economic, psychological, geographical, and demographic.
2. It supports a multi-dimensional understanding of risk perception including perceived probability, perceived severity of consequences for farms and livelihoods, and affective feelings.
3. It employs a holistic, mixed-methods approach, combining quantitative analysis to identify factors explaining risk perception variability at household level, and qualitative methods to provide deeper insights into the causal relations between factors explaining heterogeneity by community type. This approach provides a comprehensive understanding of drought risk perception.

2.2 Materials and method

2.2.1 Study area

The Tonle Sap, known as the "Great Lake" of Cambodia, is the Southeast Asia's largest freshwater lake. It plays a crucial role in supporting interconnected hydrological, agricultural and fisheries systems and dependent livelihoods (Keskinen, 2006), The lake's climate is characterized by warm temperatures and distinct seasonal patterns, heavily influenced by seasonal monsoons. The lake has a unique hydrological system resulting from alternating bi-seasonal flows. During the wet season (between June-October), the Mekong River floods and reverses the flow of the Tonle Sap River, replenishing the lake and expanding its surface area sixfold. Whereas during dry season, the Lake feeds water to the Mekong River via the Tonle Sap River. Thus, drought conditions are most common during the dry season, particularly in March and April, often exacerbated in years of low rainfall (Oeurng et al., 2019).

The lake's surface area varies from 2,500 km² during the dry season to 15,000 km² during the wet season (Matsui et al., 2005; MRC/WUP-FIN, 2007). These fluctuations profoundly affect the surrounding floodplains, influencing both agricultural and fisheries productivity in the lake and Mekong Delta. The lake supports the livelihoods of nearly half of Cambodia's population (Bonheur, 2001). Although it is well-known for its exceptional fish production, the lake’s floodplains also significantly contribute to Cambodia’s rice production, accounting for over 90% of paddy cultivation alongside the Mekong Delta region (MRC, 2014).

In recent years, the lake ecosystem has been greatly affected by climate change and human activities, particularly dam construction. Evidence of significant environmental changes include more frequent drought conditions, fluctuating water levels, and rising temperatures (Nuorteva et al., 2010; Yoshida et al., 2020), further threatening the swamp forests and fish nurseries that provide a substantial portion of Cambodia's protein (Lovgren, 2020). Fish populations decreased by over 87% between 2003 and 2019 (Seng, 2020), while shifts in water and sediments dynamics have diminished rice yields (World Bank, 2023). These changes have had profound impacts on lake-dependent livelihoods, particularly for fishers in floating villages and rain-fed farmers. Although the Mekong River Commission (MRC) and the government has prioritized drought management and established committees to address these issues, implementation at the community level remains limited due to insufficient information, expertise, and institutional capacity (MRC, 2019).

2.2.2 Study population

We studied 14 communities near by Tonle Sap Lake (Figure 7) as part of the Michigan State University (MSU) and University of Nevada, Reno (UNR) collaborative Mekong project. The villages were selected purposively selected based on village history interviews with community leaders (January 2023). Sample selection criteria included 1) proximity to the Achang irrigation dam completed in 2013 and Tonle Sap Lake, 2) majority proportion of households engaged in either farming and fishing, and 3) local livelihood concerns related to current socio-environmental challenges (e.g., land access, farming issues, decline in fisheries, relocation, migration) and a diverse set of responses to those issues in communities.

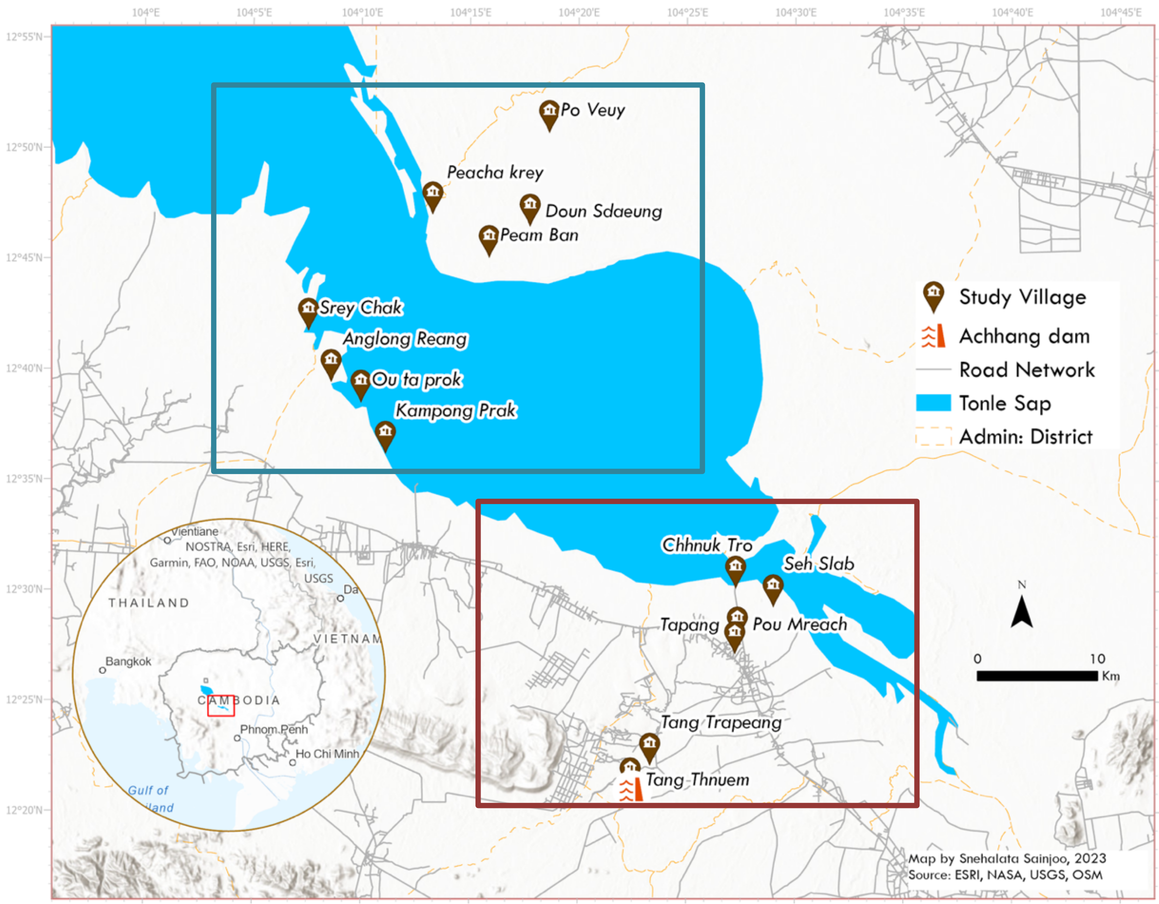


Figure 7: Study area showing sampled irrigated (orange box) and flood-pulse communities (blue box)

Eight of our study communities are geographically situated across the Tonle Sap floodplain, hence referred to as flood-pulse communities. Ou Ta Prok, Anglong Reang, Srey Chak, and Kampong Prak are located in the Pursat Province and Doun Sdaeung, Pov Veuy, Peacha Krey, and Peam Ban are situated within Beung Tonle Chhmar Ramsar and Kampong Thom Provinces. Most residents live in floating houses and rely primarily on fishing during the wet season (June-October). However, they also engage in floodplain farming and wage labor activities during the dry season (November-May) and are therefore vulnerable to the rapid ecological and hydrological changes, such as seasonal variation in water and floods (Keskinen, 2006).

The other six study communities are at different proximities to the Ajang dam, completed in 2013 and are within 15 Km of Tonle Sap Lake. We refer to these communities as irrigated communities including Trapeang and Tang Thnuem farthest upstream, Tapang and Pou Mreach in intermediate positions, and Chhunk Tru and Seh Slab farthest downstream and nearest Tonle

Sap Lake. Community members from the four communities farthest upstream are primarily from the Khmer ethnic group and engage in rice farming. The downstream communities of Chhunk Tru and Seh Slab are comprised of Cham, Vietnam, and Khmer ethnic groups and rely on fishing and wage labor. However, due to relocation efforts, some practice crop farming.

2.2.3 Research design

We employed a concurrent mixed methods approach (Figure 8) , collecting both quantitative and qualitative data simultaneously. In this design, quantitative data were gathered to explain household-level understanding of drought risk, while qualitative data provided insights into the risk dynamics by community type. These datasets were analyzed separately and then integrated in the combined Results and Discussion section 2.3, offering a broad understanding of how households perceive drought risk within the broader community dynamics.

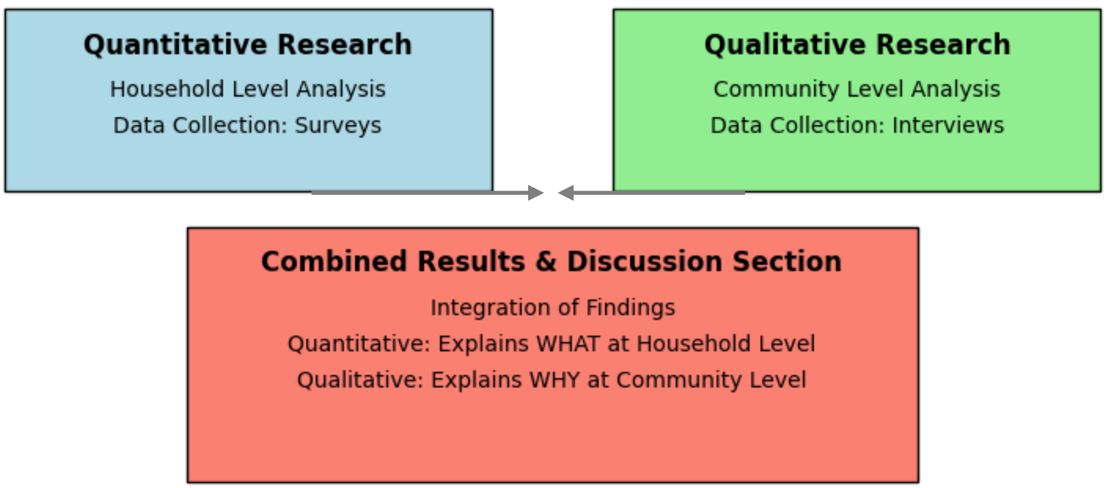


Figure 8:Concurrent mixed methods research design (Adopted from Guest & Fleming, 2015)

2.2.4 Data collection

We collected primary data between May and July 2022 utilizing a household survey, informal interviews, and field observation. Our study is approved by the Institutional Review Board (IRB) of Michigan State University (STUDY00004770). We obtained verbal consent from all participants prior to the start of data collection.

We randomly sampled 703 households for the household survey, approximately 50 households from each village. We employed tablets equipped with the Open Data Kit platform (ODK) to collect data (Hartung et al., 2010). A trained research team from Cambodia conducted face-to-face 90 minutes interview with each household head using a pretested structured and semi-structured questionnaire to collect information covering household's demographic, income and debt, material wealth, experiences to multiple shocks (such as, drought, flood, pest and diseases), drought perceptions, social networks and relations, and livelihoods including detailed information on farming, fishing, aquaculture, and livestock.

Simultaneously, the MSU research team collected qualitative information using ten informal interviews with village chief, local officials and local farmers and fishers residing nearby irrigated and flood pulse communities. We followed an exploratory approach with no predetermined selection criteria for participants. We approached individuals in each village who were knowledgeable about community practices and environmental challenges and willing to share their perspective on infrastructure development and related hydrological and ecological changes and their effects on fisheries and farms including changes to rice cropping and fishing practices, climate change, drought, coping and adaptation strategies, and local support. The interview process was flexible and inductive, allowing for open-ended conversations that helped uncover community-specific insights into these themes.

2.2.5 Variable description

a. Dependent variable

Definition Drawing on existing scholarship pertaining to farmers' risk perceptions to climate change hazards, we define perceived drought risk as the individual's subjective judgment based on the interaction of drought and individual characteristics. This conception aligns with the definition outlined in the Intergovernmental Panel on Climate Change (Field et al., 2014).

Measurement Existing studies on risk perception— grounded in different disciplines and focused on different hazard types—apply different approaches to measure risk perception. For instance, Ho et al. (2008) conceptualized risk perception as the interaction between hazard characteristics and stakeholder attributes, usings measures of likelihood, severity (including financial damage, life threat, and dread), knowledge of mitigation measures, and perceived controllability. Other studies on flood risk perception, such as those by Botzen et al. (2009) and Wilson et al. (2019a), have used Likert-scale measures to assess perceived probability of occurrence of hazard, either in absolute or in relative terms, and perceived risk to financial damage.

In climate risk studies, perceived risk is often defined through the lens of vulnerability, incorporating measures of sensitivity, exposure, and coping capacity (Conde et al., 2008). There are few studies on drought and water scarcity. Some studies, like Tang et al. (2013), have used survey items related to personal knowledge of resource status and future scarcity to measure perceived risk, while others, such as Urquijo & De Stefano (2016), have used qualitative measures, for example, the drought impacts and resource constraints faced by different water user groups.

Duinen et al. (2015) provides a case of drought risk perception in the Netherlands using measures of perceived probability of occurrence of extreme dry periods, severity to financial damage, and dread of drought. This multi-dimensional aspect of risk perception was also empirically tested across other hazard types (behavioral, technological, and climate) and was significant in explaining people's risk perception and predicting self-protective behavior (Wilson et al., 2019b). Thus, our study adopts this multidimensional framework to assess the risk perception. Mathematically, it is expressed as

$Perceived\ risk = P \times C\ (C1 + C2) \times A$------------*Equation 1*

Here, probability (P) denotes households' perceptions of the likelihood of drought occurring in the future. Consequences (C) refer to their perceptions of the severity of drought in the future in terms of financial damage (C1) and general livelihood effects (C2). Affect (A) refers to households' concern or emotion regarding future drought events. Detailed information on the survey items used to capture these measures and the corresponding responses are provided in Table 6.

Table 6: Survey items for assessing drought risk perceptions

Component	Questions	Source
Probability (P)	How likely is it that you and your farm (cropland and livestock) will experience drought or water shortages in the near future?[1] Responses in Likert scale (1-5) 1= less likely to 5= Very likely	Adapted from (Ho et al., 2008; Liu et al., 2018; Van Duinen et al., 2015)

[1] *We deliberately used both "drought" and "water shortages" in the question to ensure clarity. Previous studies suggest that locals' definitions of drought often vary, with many associating it with changes in water availability or water levels in rivers or reservoirs and hence used water scarcity to incorporate drought risk (Tang et al., 2013a). By including both terms, we aimed to capture a broader understanding and ensure that respondents accurately interpreted the question.*

Table 6 (cont'd)

Consequences (C): latent variable constructed using two observed measures, C1 and C2		
	C1: If drought or water shortages occur in the near future, how severe will your crop loss be?[2] Response in continuum of crop damage and/or loss in a scale (1-5) 1: None/insignificant loss 2: less than half 3: Half 4: More than half 5: Almost all	Adapted from (Van Duinen et al., 2015)
	C2: When you think about the possibility of drought or water shortages in the near future, what are the likely effects on you and your farm?[3]Select all that apply. Multiple options: C2.1: Financial loss, might be related to crop loss or market demand/price fluctuation C2.2: Food insecurity C2.3: Threatened health C2.4: Threatened social relationships C2.5: Increased debt C2.6: Reduced or even leave farm activities and look for other alternatives C2.7: Lost opportunity in the labor market C2.8: Even migrate for other alternatives	Adapted from (Dang et al., 2014; Udmale et al., 2014)

[2] *This question is relevant to crop farmers, particularly households residing within the irrigated communities in our study context. However, we argue that responses from households embedded in flood-pulse communities are also relevant as they are seasonally involved in crop farming.*

[3] *A majority of studies used direct and immediate effects, for example, financial loss in general (Botzen et al., 2009; Duinen et al., 2015a; Ho et al., 2008) or in terms of crop loss or income (Osiemo et al., 2021) as the measure of the severity of climate hazards. Whereas few studies capture indirect or long-term severity (Kellens et al., 2013), except for a climate risk study in Vietnam (Dang et al., 2014). Considering the invisible nature of drought with both immediate and long-term effects, in addition to severity of crop loss, we included a question that captures the long-term consequences of drought to livelihoods in general affecting health, social, and financial status.*

Table 6 (cont'd)

Affect (A)	How worried are you about the effects of drought on you and your farm in the near future? Response in Likert scale (1-5) 1= Less to 5= High	Adapted from (Rana et al., 2020; Van Duinen et al., 2015; Wilson et al., 2019b)

Risk perception score To calculate a drought risk perception score, we applied confounding factor analysis (CFA), a widely used approach in risk perception studies, particularly when there is an existing underlying structure for validation (Johnson & Kim, 2023; Walpole & Wilson, 2021; Wilson et al., 2019). Following this scholarship, we developed a three-factor model using two observed variables (P and A) and one latent variable (C), as shown in Figure 9. The observed variables (indicated in square boxes) are those directly measured, while the latent variables (indicated in ellipses) are not directly observed or measured and are inferred from a set of observed variables (C1 and C2). To validate our three-factor modeling approach, we also conducted an exploratory factor analysis.

We began by checking the basic assumptions for factor analysis, including the Measure of Sampling Adequacy (MSA) using the Kaiser-Meyer-Olkin (KMO) test, and the significance of the multiple correlations using Bartlett's test of sphericity. The calculated MSA (0.6) suggests that the sample adequacy is moderate but acceptable (Kaiser, 1974). Significant results at *p-value* <0.05 from Bartlett's test of sphericity indicates that the variables included are suitable for factor analysis (Bartlett, 1951). Then, we determined that three factors should be extracted using parallel analysis. All analyses were conducted using the *psych* package in R.

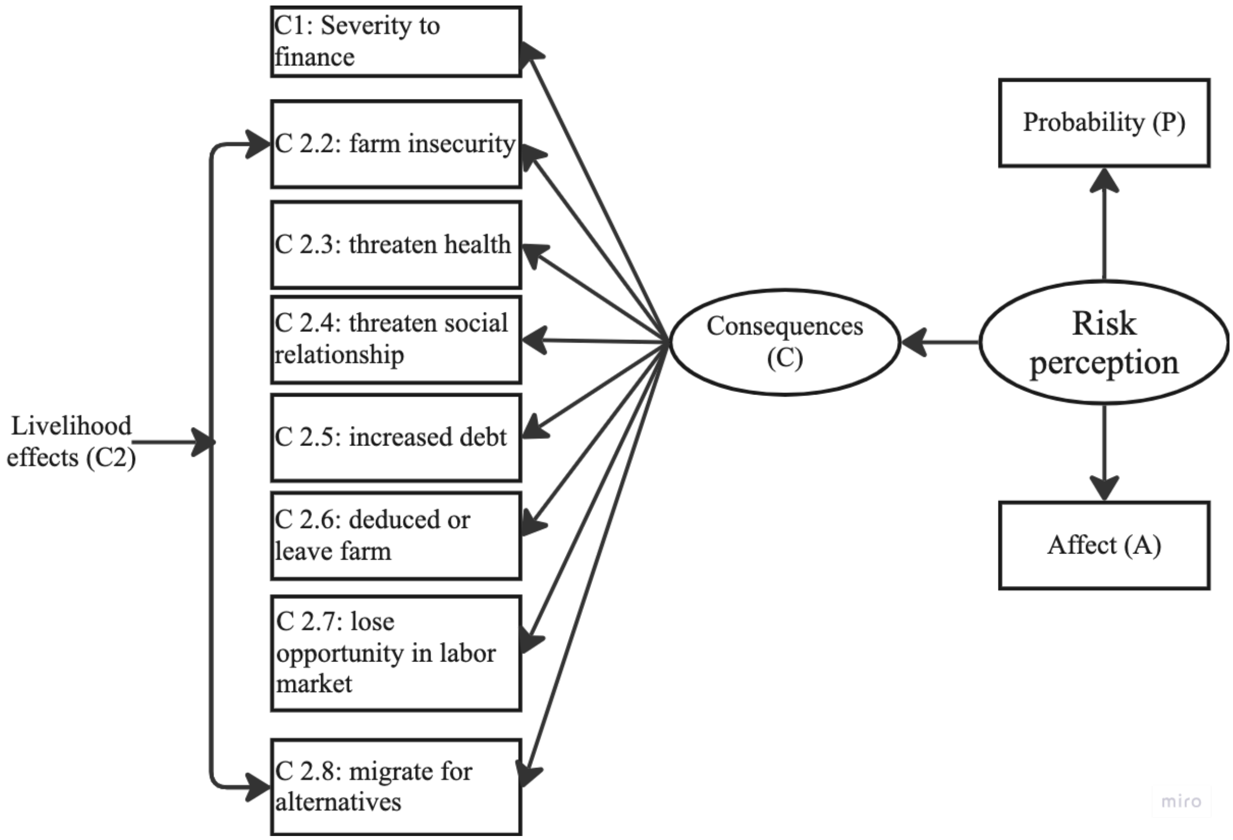


Figure 9: Risk perception model

Following statistical validation, we used a three-factor model structure that conceptualizes perceived risk as a function of probability, consequences, and affect. We first built the measurement model associated with "consequences (C)" using observed measures (C1 and C2). We then constructed the risk perception model using a three-factor framework: P, C, and A (Figure 9). We utilized the *lavaan* package in R (Rosseel, 2012) and employed the weighted least squares mean and variance adjusted (WLSMV) estimator for both models (C.-H. Li, 2016). The goodness-of-fit indices ($\chi^2 = 322.699$, $p < 0.001$, CFI = 0.85, TLI = 0.82, RMSEA = 0.09) suggest a reasonable fit between the risk perception model and the data (Hu & Bentler, 1998). Finally, we extracted the standardized risk score using the first principal component eigenvalues. Subsequently, we categorized households' perception of risk into four quintiles, corresponding to low, medium, high, and very high levels of perceived risk.

b. Independent variables

We included a set of key predictors that could explain the heterogeneity in risk perception at the household level. Details on hypotheses specific to each predictor are provided in sub-section 1.3.

Biophysical factors include 'presence of external water source', which was measured as a binary variable based on whether the household reported having access to an external water supply for drinking and household use (Yes=1), for example private and communal tap, well, and market store.

Experiential factors include households' previous experience with drought, which was measured as a binary response to whether household members and their farm faced drought in the past few years (Yes = 1, No = 0).

Social factors include 'social ties' for farming related information and 'membership to any organizations.

- Social ties for information were measured as a binary response to whether households received information related to cultivation, fishing and livestock from formal or informal ties (Yes=1, No=0).
- Membership to any organizations was measured as a binary response to whether household members were members to any of the groups or organizations: farm-association-or-cooperative, fish-association-or-cooperative, women's organization, water-use organization, irrigation organization, seed bank, religious group, political group, or credit or finance group (Yes=1, No=0).

Economic factors

We used a wealth index as a proxy measure of **economic** condition. The wealth index is constructed using Principal Component Analysis (PCA) (Córdova, 2008; Howe et al., 2008) based on nine observed measures. These measures include the total number of durable assets owned by the household; total number of farming and fishing equipment; access to an improved source of drinking water, an improved source of fuel for cooking and lightening, toilet facilities (1=flush latrine, 0=0 = pit over lake or share or none); amount of land owned (ha); and total livestock units (TLU). A higher value indicates higher wealth.

TLU represents the weighted sum of domestic animals owned. TLU is a standardized metric of total livestock owned using a weighted value for each species as provided by FAO (2005) in the Cambodian context: 0.65 for cattle, 0.7 for buffalo, 0.1 for sheep and goats, 0.25 for pigs, and 0.01 for chickens/poultry.

Psychological factors include 'subjective knowledge', 'trust', and 'perceived ability.'

- Subjective knowledge of drought is measured using an index value created using principal component analysis (PCA) based on measures of drought causes (i.e., insufficient or irregular rainfall, excessive water use, upstream dam construction, and inefficient water distribution) and drought effects (i.e., reduced food supply, decreased income, conflicts over water, lowered river or lake water levels, decreased groundwater availability, and reduced water quality) (Shi et al., 2016). Responses to each cause and consequence, for example, *is insufficient rainfall as the cause of drought*, was recorded as binary response (Yes = 1, No = 0). Overall, a higher index value indicates greater subjective knowledge of drought within the household.
- Trust in government agencies was measured as a binary variable (1 = Yes, 0 = No) based on household responses to whether existing water governance organizations are effective in managing droughts.
- Perceived ability was measured using a Likert scale in response to the question, "Earlier, you indicated how drought might affect you and your farm. How confident are you in your ability to deal with those problems?" with responses ranging from 1 = not confident to 5 = very confident (adapted from Gebrehiwot & van der Veen, 2015).

We also considered geographical factors (referred as 'community type') including household's proximity to either a nearby irrigation canal (Irrigated=1) or flood-pulse zone (Flooded=0). Further, we controlled for household demographic factors including household head age (years), sex (1=Female, 0=Male), education (any formal education: Yes=1, No=0) and ethnicity (1 = Khmer, 0 = Non-Khmer). Table 7 provides summary statistics for all predictors.

Table 7: Summary statistics for the model predictors

Predictors		Mean/ Frequency (%)	SD	Min	Max
X_1: Presence of external water source	Yes =1	18.3%		0	1
	No =0	81.7%			
X_2: Social ties	Yes =1	85.3%		0	1
	No =0	14.7%			

Table 7 (cont'd)

X_3: Membership to any organization	Yes =1	16.6%		0	1
	No =0	83.4%			
X_4: Wealth index		0	1	-2.6	2.8
X_5: Previous experience to drought	Yes =1	81.9%		0	1
	No =0	18.1%			
X_6: Subjective knowledge		4.1	1	0	7.5
X_7: Perceived ability		1.8	1	1	5
X_8: Trust in government	Yes =1	10.7%		0	1
	No =0	89.3%			
X_9: Community type	Irrigated =1	28.4%		0	1
	Flooded= 0	71.6%			
X_{10}: Age (Years)		45.4	13.4	20	86
X_{11}: Sex	Female =1	15.6%		0	1
	Male=0	84.4%			
X_{12}: Education	Yes =1	72.5%		0	1
	No =0	27.5%			
X_{13}: Ethnicity	Khmer =1	93.0%		0	1
	Non-Khmer =0	7.0%			

2.2.6 Analytical approach

Quantitative

We applied a mixed effect model, a two-level hierarchical linear model (HLM) using the *lme4* package in R to examine the effects of the predictors at the household level on household' perceived risk while accounting for community-level variation. HLM is typically utilized with nested data and accounts for the possibility of covariate effects at different levels on the response variable. For our data, the household risk perception score (i) is nested within communities (j=14).

We followed guidelines of the general multilevel model by Steenbergen & Jones (2002) and Snijders & Bosker (2011) for model identification. We began by conducting a random effect

ANOVA analysis at the 5% level of significance (Null model). We found the random intercept value significant, indicating significant variability in risk scores across communities. We followed by computing the interclass correlation coefficient (ICC) value. The calculated ICC value of 0.132 suggests that approximately 13.2% of the total variability in the perceived risk score is accounted for at the community level, suggesting strong consideration of a multilevel modelling approach (Hedges & Hedberg, 2007). We proceeded with the random intercept fixed-effect model where we considered the variability between communities, measured by a random intercept, but we fixed the effects of household level predictors. Compared to the typical OLS regression model, model estimates are reliable and address type I errors and ecology fallacy (Snijders & Bosker, 2011; Steenbergen & Jones, 2002).

The fitted full model (M1) is specified as

$$y_{ij} \ = \gamma_{00} + \sum_{k=1}^{13} \beta_k \, X_{kij} + \mathrm{u}_{0j} + \varepsilon_{ij} \text{ ----------Eq (1)}$$

Where

y_{ij} denotes the household level perceived drought risk score, the household level (level 1) predictors are denoted as Xkij (l = 1, 2, . . . , 15), and eijk ∼ N(0, σe2) is the error term.

γ00 is the regression intercept or grand mean y_{ij} measuring perceived risk while controlling for the effects of all levels 1 predictor variables (see detail list in Table 2). β_k is the effect for each predictor variables on perceived risk. u_{0j} is random intercept for the community j (level 2) which capture variability between communities; whereas ε_{ij} is the error term for individual i within community j), captures variability at household level.

In our study, we included the interaction between two predictors- wealth index (X_4) and perceived ability (X_7). Thus, the fitted full model with interaction (M2) is specified as

$$y_{ij} \ = \gamma_{00} + \sum_{k=1}^{n13} \beta_k \, X_{kij} + \beta_{14}(X_{4ij} \times X_{7ij}) + \mathrm{u}_{0j} + \varepsilon_{ij} \text{ ----------Eq (2)}$$

Where, β_{11} is unstandardized coefficient for the interaction term $X_{4ij} \times X_{7ij}$.

The significance of the models is tested using a likelihood ratio test (LRT). Thus, each time, the null model is compared with alternative models including a full model with 13 predictors (M1) and full model with an interaction term (M2). We also calculated Akaike's Information Criteria (AIC) to identify the model that provides the best explanation of households' perceived risk. Further, we calculated the proportion of variation explained at level 2 compared to our null model, using the equation:

$$Additional\ variation\ explained = \frac{Total\ variation\ (M2) - Total\ variation\ (M1)}{Total\ variation\ (M2)}$$ ------Eq (3)

Qualitative

While the quantitative approach is effective in explaining what explains heterogeneity in risk perception at households' level, it is limited in capturing the deeper, context-specific reasons behind these variations by community type. To address this limitation, we applied qualitative methods, which allow for a nuanced exploration of the underlying bio-physical, household and institutional factors and causal mechanisms at play.

We adopted a thematic approach for coding qualitative data, following recommended thematic analysis procedures (Miles et al., 2014) to extract and label meaningful themes (i.e., code) and concepts from responses to semi-structured questions. The Cambodian research team transcribed (Khmer) and translated (English) all recorded qualitative responses from 3,700 audio files beginning with a subset of 20% of files. Both the Cambodian and Michigan State University (MSU) teams then identified themes and concepts resulting in codes, which were then applied to the subset of audio files to validate code applicability. Over three rounds of collective discussion, iterative coding adjustments, and determinations of high inter-coder reliability, a final set of codes, specified to each open-ended question, were developed, and applied to all responses.

We developed summary statements from qualitative data collected using informal interviews by extracting key sentences or paragraphs corresponding to each code. These statements served as anecdotes, suggesting underlying reasons or mechanisms for behaviors noted by participants.

Finally, we used narratives from interviews to construct a causal loop diagram (CLD) that integrates various biophysical, institutional, and household-level factors which might explain persistent behavior related to drought severity over time across different community types. CLD is a qualitative modeling approach that is particularly effective for identification of the root causes of recurring problems, known as "system archetypes"(Mirchi et al., 2012). Studies increasingly use CLD in examining system archetypes such as drought or water problems. For instance, CLD was used as a base model to explore the causal interactions, identify archetypes, and explain recurring behaviors in contexts like drought in rainfed agriculture in Iran (Shahbazbegian & Bagheri, 2010), coffee production systems in Vietnam (Y. Pham et al., 2020), and water scarcity in Iran (Barati et al., 2023).

In our study, the CLD establishes the preliminary causal hypotheses regarding the perceived trends in drought severity over time, which may help explain the heterogeneity in risk perception across different community types. It is important to note that the CLD represents the subjective nature of community-level responses and perceptions derived from interview narratives, rather than a deductive analysis of all possible factors. As such, while institutional factors are included, broader roles such as government involvement may not be fully represented.

We developed two CLDs to represent the irrigated (CLD-I) and flood-pulse communities (CLD-F). Using Stella software, we linked the identified variables, illustrating how one variable affects another. The links are labeled with either a "+" or a "-" based on the direction of the relationship, positive or negative. When a causal link demonstrated a reciprocal relationship, we created a feedback loop, which could be either balancing or reinforcing (Barbrook-Johnson & Penn, 2022). Finally, we assembled all feedback loops into a causal loop diagram to create a visual model of perceived drought severity behavior.

2.3 Results and discussion

2.3.1 Drought risk perception

From our random intercept model, we found significant variability in farmers' perception of drought risk both within and across communities. The standard deviation of the random intercept, which measures variability between communities, was estimated at 0.167 (95% CI: 0.073, 0.242; variance = 0.028). This indicates notable differences in risk perception between communities. Additionally, the standard deviation of the residuals, capturing variability within communities, was estimated at 0.642 (95% CI: 0.600, 0.667; variance = 0.412). This highlights substantial differences in risk perception among farmers within the same community.

Looking at the importance of individual characteristics on drought risk perception, our Confirmatory Factor Analysis (CFA) results revealed varying degrees of factor loadings across three dimensions. The severity of consequences to households' finances and livelihoods emerged as the most significant factor, with a high loading of 0.80. In contrast, affective responses to drought showed a moderate loading of 0.53, and the perceived probability of drought occurrence exhibited the lowest loading at 0.49. These findings suggest that households place greater emphasis on the potential impacts of drought when shaping their risk perceptions, followed by emotional responses and, lastly, their assessment of the likelihood of drought occurrence.

Previous studies have similarly highlighted the strong effect of consequences and emotional factors in forming risk perceptions, while consistently noting the relatively lower influence of perceived probability (Tang et al., 2013b; Wilson et al., 2019).

Overall, we found that a majority of households—approximately 72%— fall into the perceived risk categories of high or very high. Figure 10 provides the response to each characteristic of drought.

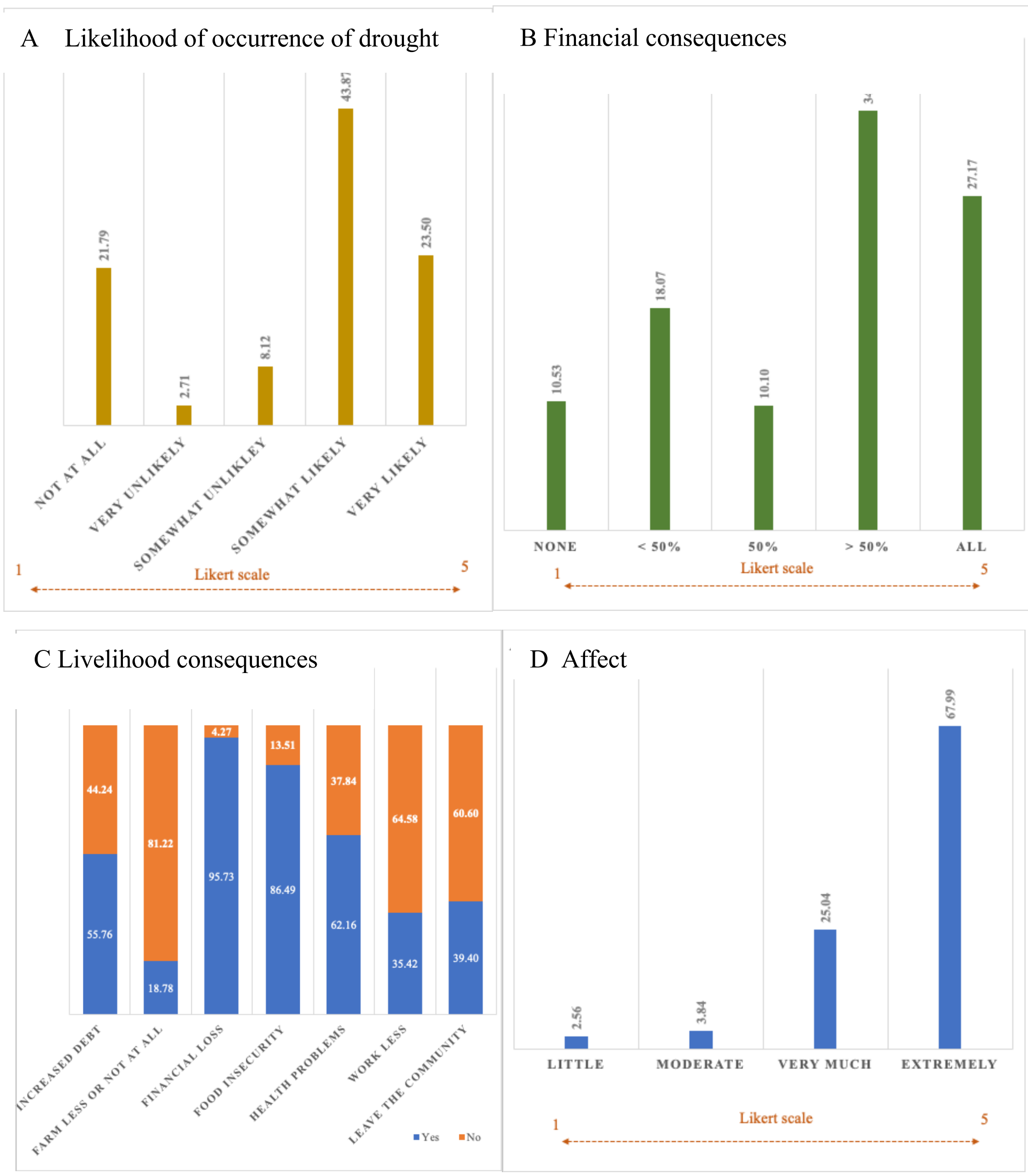


Figure 10: Households' response to different component of drought risk

Around 67% of households reported that it is somewhat to very likely that they and their farm would experience drought or water shortages in the near future (Figure 10A), and they are extremely worried about effects (Figure 10 D). When considering the severity of future consequences, more than half of the households anticipated substantial crop losses with over 50% expecting losses ranging from half to their entire crop yield (Figure 10B). In terms of effect to livelihood, a majority reported that they might face financial loss (around 96%), food insecurity (around 86%), health related problems (62%) and debt (around 56%) (Figure 10C). Dang et al. (2014) found similar observation among farmers in Vietnam, reporting perceived climate risk to their production, income and physical health.

When comparing the average risk perception across different communities, we found that communities located near irrigated dams perceived higher drought risk compared to those in the flood-pulse zone (Figure 11), an observation supported by the findings from our mixed-effect model, discussed in the following section.

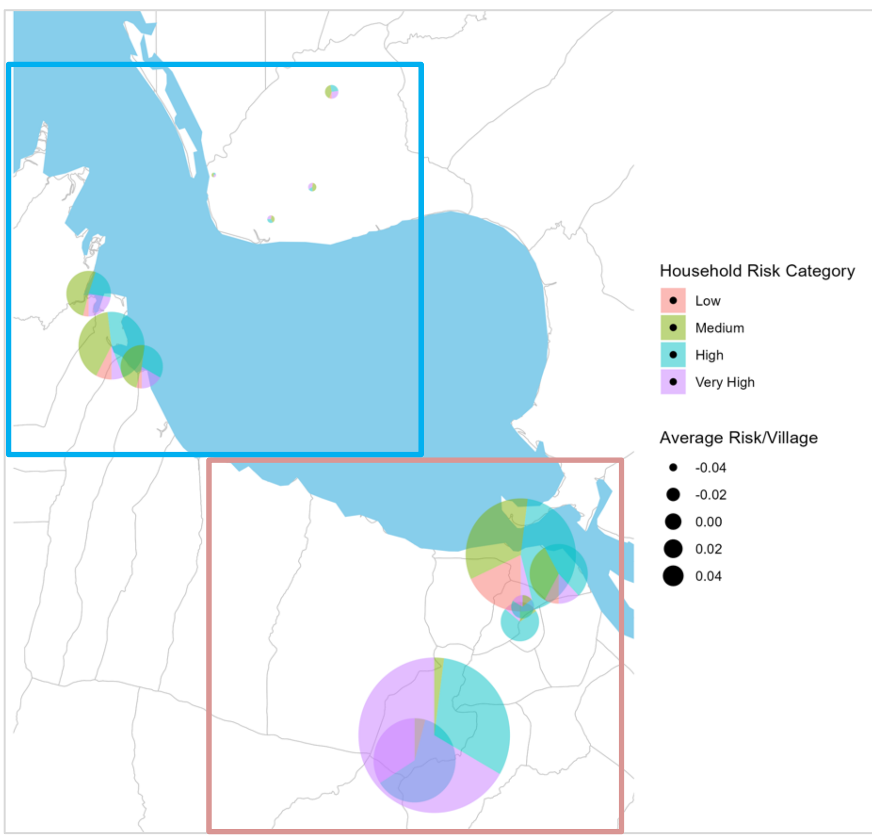


Figure 11: Distribution of perceived drought risk by household and community type
[*Note: Pie charge shows the distribution of household risk categories. The size of the pie chart indicates the mean value of perceived risk score with larger pies denoting higher perceived risk. The orange and blue boxes identify irrigated and flooded communities respectively*.]

2.3.2 Household level shaping factors

Table 8 shows the results of three nested models, including a null model and a full model without (M1) and with interaction term (M2).

Table 8: Summary estimation results of the linear mixed-effects model (N=703)

Predictors	Null model	Model without (M2)	Model with interaction (M3)
Presence of external water source [Yes=1]		-0.04	-0.01
		(0.07)	(0.07)
Previous experience to drought [Yes=1]		0.1	0.09
		(0.07)	-0.07)
Subjective knowledge		0.10***	0.09***
		(0.03)	(0.03)
Perceived ability		0.26***	0.27***
		(0.02)	(0.02)
Wealth index		-0.06	0.09
		(0.04)	(0.06)
Trust in government [Yes=1]		0	0
		(0.08)	(0.08)
Membership to any organization [Yes=1]		-0.52***	-0.46***
		(0.07)	(0.07)
Social ties [Yes=1]		0.18*	0.17*
		(0.08)	(0.08)
Sex [Female=1]		0.09	0.1
		((0.08))	(0.07)
Age (Yrs.)		0	0
		(0)	(0)
Education [Yes=1]		-0.02	-0.02
		(0.06)	(0.06)
Ethnicity [Khmer=1]		0.18	0.2
		(0.11)	(0.11)
Community type [Irrigated=1]		0.39**	0.41**
		(0.13)	(0.13)
Interaction term			-0.08***
(Perceived ability * Wealth index)			(0.02)
(Intercept)	0	-0.36	-0.34
	(0.08)	(0.32)	(0.31)
AIC	1630.43	1470.76	1467.25
Log Likelihood	-812.21	-719.38	-716.62
LRT χ^2 (p-value <0.001)		42.83	11.562

Notes: The table reports the unstandardized beta coefficient of the mixed-effects linear regression model with community random effects and fixed effect of predictors at level 1. The standard errors are in parentheses. ****, **, * , ' showing significant at <1%, 1%,and 5%.*

The likelihood ratio test (LRT) indicated that each subsequent model is statistically significant in comparison to the previous model. Further, there is no difference in proportion of variation explained at level 2 when we compared M1 and M2 to the null model. However, upon comparing AIC, we identified the full model with an interaction term (M2) as the best choice to explain the effect of household level factors on risk perceptions.

Starting with psychological factors, we only find significant effects of subjective knowledge and perceived ability on households' perception of drought risk.

Subjective knowledge The coefficient ($\beta = 0.09$, $p < 0.001$) indicates that for every one-unit increase in subjective knowledge about the causes and consequences of drought, perceived risk increases by 0.09, holding all other variables constant. This finding highlights the importance of subjective knowledge in raising awareness about drought risks, which could potentially lead to more proactive adaptation measures.

This result is consistent with prior studies highlighting the impact of knowledge, particularly perceived causes of hazards on risk perception. For example, Shi et al. (2016) found that higher levels of knowledge, particularly about the causes of climate change, significantly heightened concern about climate change across several countries including China, the UK, Japan, the USA, Canada, and Switzerland. Similarly, Botzen et al., (2009) reported that a lack of knowledge about the causes of flood events lowered flood risk perception among people in the Netherlands, affecting their mitigation actions, for example purchase of insurance.

Our findings contribute to this body of work by reinforcing the argument that enhancing domain-specific knowledge—like understanding the causes and consequences of drought—can influence risk perceptions. While our study did not directly compare these perceptions to expert assessments, the observed relationship supports the idea that better-informed individuals may have risk perceptions that align more closely with expert views, thereby fostering more effective risk communication and adaptive behaviors (Siegrist & Árvai, 2020).

Perceived ability Our results suggest that household perceived risk is likely to increase by 0.27 score with every unit increase in households' perceived ability to handle the impacts of drought in the future ($\beta = 0.27$, $p < 0.001$). This finding contrasts with our initial hypothesis and some previous studies such as Van Duinen et al. (2015) who reported a negative association between perceived control over drought effects and perceived risk in Netherlands. Similarly, Sjöberg (2000) suggested a linear relationship between control over various hazards and risk aversion among a Swedish population. Sjöberg (2000) explains this inverse effect as possibly due to an "overconfidence effect," where individuals with a high sense of control may underestimate risks associated with other factors, leading to what is known as "risk denial." They might believe that their actions or decisions can prevent negative outcomes, leading to a lower perception of risk.

However, it is important to note that the relationship between perceived ability and perceived risk can vary depending on hazard type. For example, Ho et al. (2008) found an inverse relationship between a sense of controllability and perceived impact for landslides, where a single effective measure, evacuation, exists. In contrast, for floods, where people take various precautions but still face recurring financial losses, the situation is perceived as less controllable. In our study context, this suggests that a higher perceived ability to manage drought could still be associated with increased perceived risk, especially as drought events become more frequent and damaging.

Wealth condition and perceived ability We did not find a direct effect of wealth on perceived risk. However, we did observe a significant moderating effect of wealth on the relationship between perceived ability and perceived risk (Figure 12).

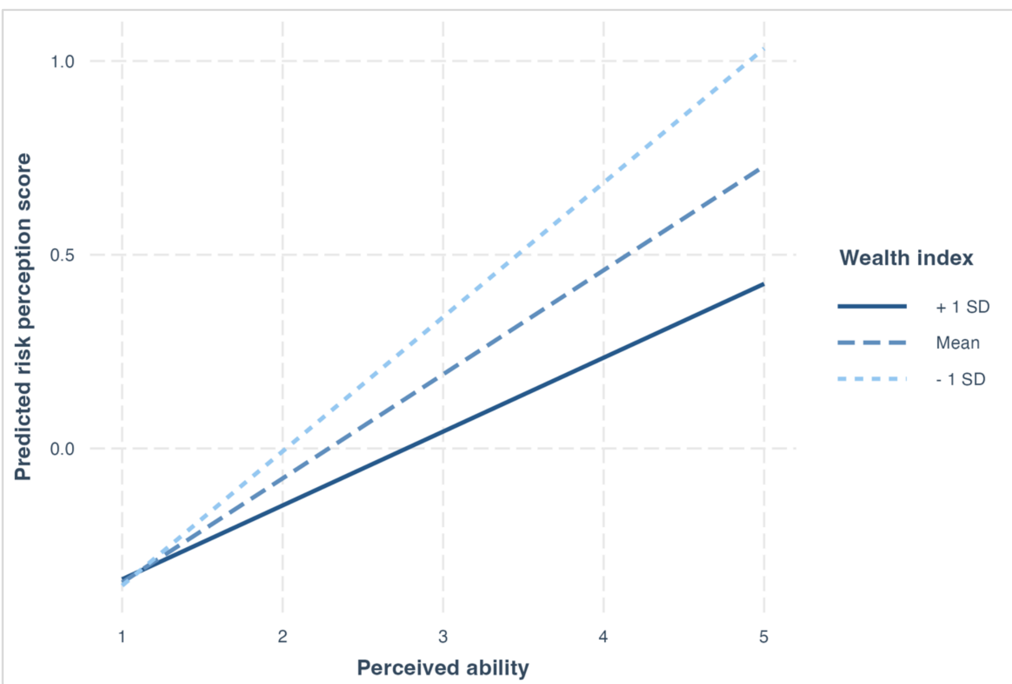


Figure 12: The marginal effect of wealth on the relationship between perceived ability and risk perception

The interaction plot shows a positive linear relationship between perceived control and perceived risk across all wealth levels. However, this relationship varies with wealth: at lower wealth levels (mean -1 SD), the slope is steeper, indicating a stronger relationship between perceived control and perceived risk. Conversely, at higher wealth levels (mean +1 SD), the slope is gentler, suggesting a weaker relationship. Therefore, as households become wealthier, the positive relationship between perceived control and risk perception may weaken. A possible explanation, as suggested by Slovic (1987, 2000), is that financial resources enable individuals to manage and control risks more effectively, thereby providing safeguards against losses. This, in turn, could reduce their overall perceived risk.

Looking at social factors, we find significant effects of social ties for information and association to any organization on households' perceived risk but with opposite relationships.

Social ties for information The estimate suggests that information obtained from both formal and informal social networks positively influences household perception of drought risk, with a 0.17 times higher likelihood compared to those without such ties ($\beta = 0.17$, $p < 0.05$). This finding is consistent with previous studies that demonstrate how connections to social networks increase awareness and heighten risk perception (Dang et al., 2014; Tang et al., 2013a; Wachinger et al., 2013). Specifically, informal ties, such as those with friends, relatives, and neighbors, have been shown to amplify perceived risk by raising awareness and triggering memories of past events, such as droughts, further emphasizing the primary role of social networks in risk communication.

Association to any organization In contrast to the effect of social ties, we find a negative association between one's association with different organizations and drought risk perception ($\beta = -0.46$, $p < 0.001$). This may be because, unlike households' social ties for information, households' associations with various organizations—such as farm or fish cooperatives and credit groups— might primarily involve accessing material, financial and technological supports. These supports likely enhance their adaptive capacity (Adger, 2003; Bastakoti et al., 2014), thereby increasing their perceived control over impacts (Burnham & Ma, 2017), and as a result, lowering their perceived risk.

Geographical factor We found a significant effect of community location on drought risk perception. The estimate suggests that households located in communities near irrigation dams perceive 0.41 times higher risk compared to those in communities in the flood-pulse region. While this finding is novel in risk perception studies, earlier scholars have highlighted the importance of contextual factors in shaping flood risk perception. For instance, Botzen et al.,

(2009) identified geographical characteristics, such as proximity to a main river and rural location, as key determinants in shaping households' perceptions of flood risk and expected damage. Similarly, in the farming context, studies have found that farmers perceive risk through their exposure to resource constraints like water scarcity (Tang et al., 2013a) or uncertainty with existing water sources, such as surface water (Urquijo & De Stefano, 2016).

Considering these findings, it is plausible that in our study context, households located closer to irrigation canals may perceive higher drought risk due to their reliance on irrigation infrastructure As drought events become more frequent, these households though located nearby irrigation canal, may face exacerbated impacts, such as crop loss and increased expenses, as they experience variable and inconsistent distributions of irrigation water. This causal relation is further explored using qualitative information and CLD, as detailed in section 3.3.

2.3.3 Heterogeneity in risk perception by community type

Figure 13 and Figure 14 show the potential interconnected biophysical, institutional, and household-level factors that may explain why households in irrigated communities perceive a higher risk compared to those in flood-pulse communities.

There are two reinforcing and one balancing loops in CLD-I that explain the recurring pattern of drought severity in the irrigated communities (Figure 13).

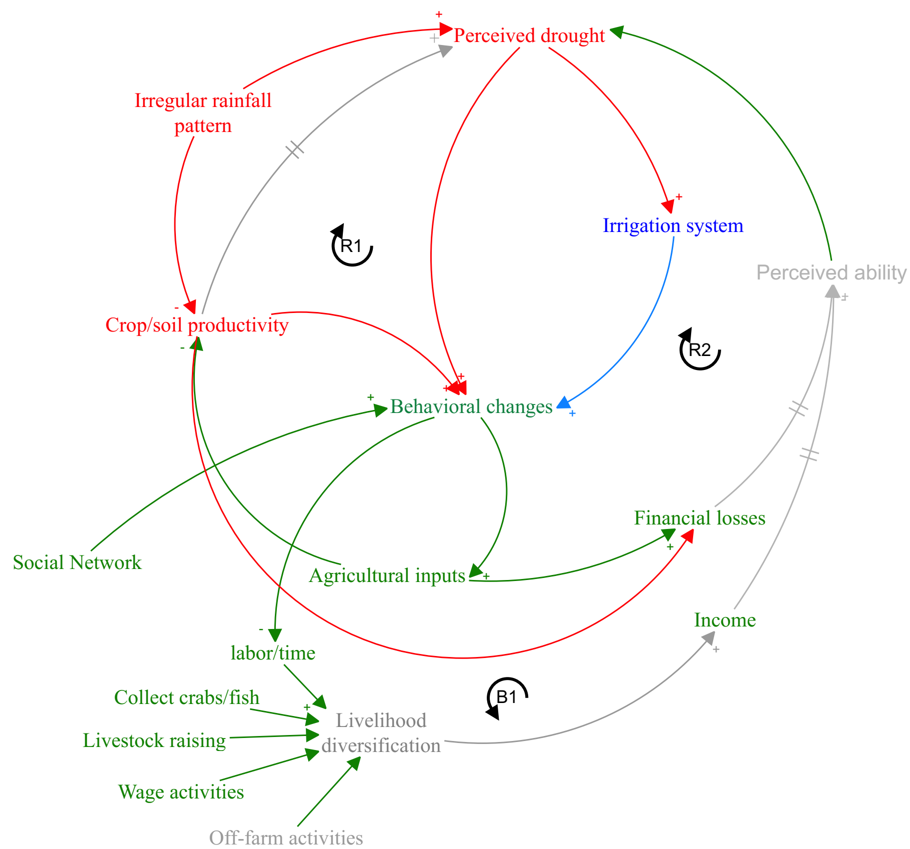


Figure 13: CLD-I showing the interrelated factors that reinforce the perceived drought severity/risk in the irrigated communities (source: Field survey, 2022)

[*In the diagram, red text denotes biophysical factor, blue denotes institutional and green denotes the household factors. Grey text denotes the likely factors connecting dots between factors from interview narration. Arrow with double slash (//) shows the lag effect in the system.*]

The **first reinforcing loop (R1)** operates as follows: As farmers perceive an increasing trend in drought severity (‘*perceived drought*’), they make various changes in cultivation practices, referred to as "behavioral changes." Despite these changes, they experience a decline in ‘*crop productivity*’, which is likely to heighten their ‘*perceived drought*’ severity risk. This loop is supported by interview narratives. Locals reported an increasing trend of irregular rainfall patterns and short-term droughts during the wet season over last three years, facing significant crop losses. Around 96 percent of farmers reported experiencing drought in the last year. As a result, the majority have shifted from long-term transplantation to the short-term broadcast method for rice farming during the wet season. This shift has led to subsequent changes in other cultivation practices such as changes in crop varieties and increased application of pesticides, herbicides and fertilizers. However, despite their efforts, they continue to face declining in crop productivity.

One interviewed farmer echoed this experience:

> "*When I changed from long term to short term rice, I got less yield. Because of drought*, *we lost crops, but I think it is better to practices short term as I can assure the yield at least, though the yield is less*." (Women, 35, Khum Ponley)

This narrative suggests that farmers may continue using the new method, increasing their investment, but in the long run, they might face a decline in soil productivity, losing more crops, which could further increase their perception of drought severity.

The **second reinforcing loop (R2)** connects '*perceived drought*', the '*irrigation system'*, and '*behavioral changes.*' Although these communities are located near irrigation canals, only 34 percent of households have access to irrigation water (HH survey, 2022), indicating an unequal distribution of irrigation resources. In this context, farmers—both those who have access to irrigation water and those expecting it in the future—make changes in their cultivation practices. Similar to R1, these new methods and subsequent incremental changes increase their investment. However, as they face declining crop production and recurring losses over time, they may perceive the situation as less controllable ('perceived ability' decreases), further amplifying their perception of drought severity.

One farmer's experience reflects this challenge:

> "*Rice farming doesn't provide a good profit because fertilizer is quite expensive, but the price of rice is really cheap. I am in debt now because I make a loss in farming."*

The **balancing loop (B1)** introduces a potential connection based on farmers' narratives about reallocating labor and time to other livelihood activities. Many farmers reported that by using the broadcast method instead of transplantation, they saved time and labor. This shift allows them to engage in additional activities, as illustrated by one farmer's statement:

> "*I changed farming practices from transplantation to broad cast. There is increased application of equipment like tractors to farm, compared to past when I used to use cattle. Because of that I could reduce the labor. I have more free time to do other works, for example, wage labor in construction*." (Woman, 36 years old, Tang Thneum)

Referring to this statement, we can expect these farmers might diversify their livelihood activities —such as fish and crab collecting, wage labor, and small business ventures—by reallocating labor time. This diversification could increase their financial resources. which, although they may still experience crop losses, might help them better manage the financial impact of drought. Over time, this could enhance their perceived ability to control the situation, ultimately reducing their perception of drought severity.

Unlike CLD-I, we did not identify any feedback loops in CLD-F that explain the behavioral patterns of drought in the flood-pulse communities (Figure 14). However, CLD-F is still useful in understanding the possible disconnection between factors that might explain why perceived drought risk is lower among households that primarily rely on fishing.

We find that fishers are aware of climatic and environmental changes, such as irregular rainfall, changes in flooding/water levels, and increases in temperature. They can clearly relate these changes to institutional factors (e.g., government policies restricting fishing) and household factors (e.g., illegal fishing) affecting fish population and diversity. Additionally, some local fishers, consistent with conservation officers, link drought with changes in water levels that affect fish populations.

However, when discussing the factors affecting fish availability for catch, the majority pointed to illegal fishing (around 75% based on qualitative response from 212 HH on question "*Why do you think the availability of these fish has decreased in the past few years?*"), which is likely to be driven by government policies restricting fishing in Tonle Sap Lake. These policies, such as seasonal fishing bans, area closures, or restrictions on fishing gear, were designed to allow fish stocks to recover. However, unintended consequences have emerged as many fisher, particularly those who rely heavily on fishing for their livelihood, have struggled to comply with these restrictions due to a lack of alternative income sources. As a result, these fishers often turn to illegal fishing as a means of maintaining their livelihoods (Gerald Flynn, 2022). This illegal fishing is characterized by practices such as fishing during prohibited seasons, using banned gear, or entering protected areas. Weak enforcement of these restrictions allows these practices to persist (Trenchard, 2023), further depleting fish stocks over time(R1). The narratives do not support any link connecting change in fish harvest for their livelihood and perceived drought severity.

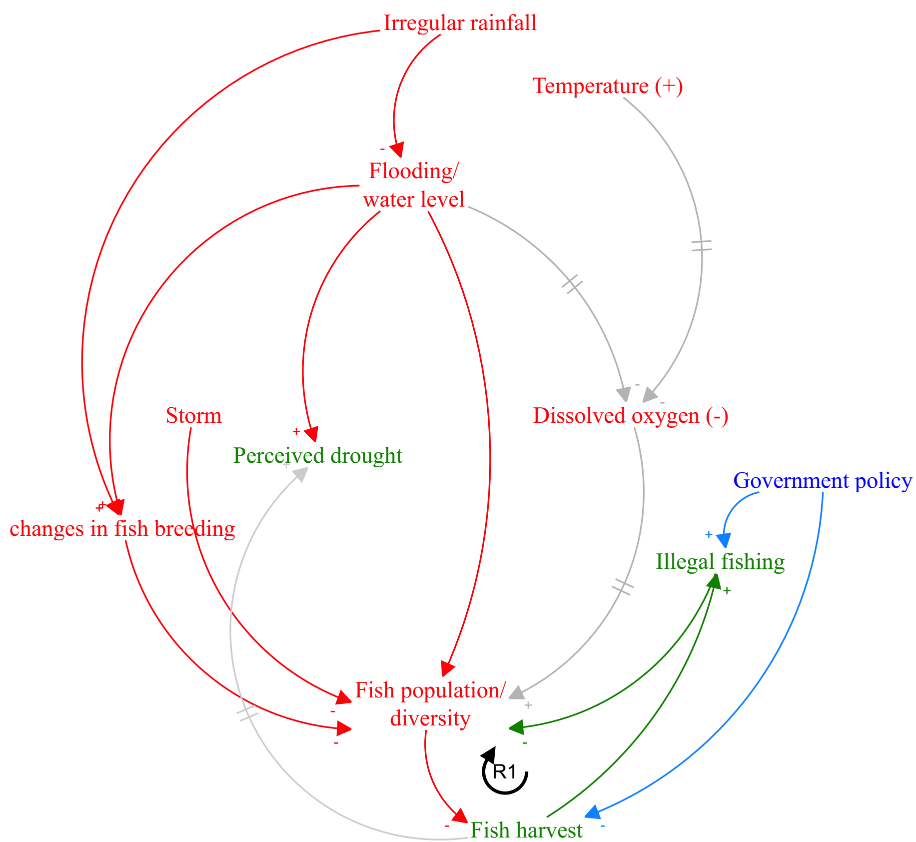


Figure 14: Casual loop diagram showing the interrelated factors impacting fishing and potential link explaining perceived drought risk in Flood-pulse fishing communities

We hypothesize that this disconnect may stem from the delayed effects within fisheries, where the impacts of drought on fish populations are not immediately apparent (Brown et al., 2012). This delay might prevent fishers from fully recognizing the long-term consequences of drought on their livelihoods, which could explain their lower perceived risk (Slovic, 2016). Additionally, other pressing stressors, such as illegal fishing, may overshadow the effects of drought. As a result, fishers might overlook or underestimate the connection between declining fish harvests and drought severity, resulting in a relatively lower risk perception. Further research is needed to explore these dynamics in greater depth and provide clearer insights.

Overall, these insights are valuable for future research and policy initiatives. Specifically, our findings contribute to the development of context-tailored drought risk communication and management strategies, aligning with objectives outlined in "2021–2030 Basin Development Strategy and Mekong River Commission Strategic Plan 2021–2025 " for drought management in the Mekong region. Such strategies can support vulnerable farming and fishing communities in managing drought risk while addressing potential socioeconomic disparities in the region.

2.4 Way forward

In this study, we examined how households—nested in communities among different contexts—understand drought risk, revealing significant variation in risk perception both within and across communities. This variation is shaped by socio-economic and psychological factors, including subjective knowledge (e.g., understanding the causes and consequences of drought), perceived ability to cope with drought impacts, wealth status, social ties for information exchange, association with different organizations, and community characteristics (such as proximity to irrigation canal and flood-pulse zone).

Our findings highlight the importance of increasing awareness of drought causes and consequences to improve risk perception, which could support more effective adaptation actions. Additionally, we observe that social ties play a positive role in sharing information, thereby enhancing knowledge and increasing risk perception. Conversely, the negative effect of one's association with different organizations on risk perception suggests that these associations might support building capacity of household to manage risk, thereby lowering their risk perception. The moderating effect of wealth on perceived ability and risk perception suggests that those with limited financial resources tend to have higher perceptions of risk, as they feel less control over their situation. Conversely, wealthier individuals may perceive greater control, potentially leading them to underestimate risk and overlook necessary adaptation measures. This indicates a need for targeted risk communication and management programs that effectively address drought across all socioeconomic groups.

Interestingly, we find heterogeneity in risk perception across communities, with higher perceptions of risk among irrigated communities compared to those located around the Tonle Sap Lake. This difference can be explained by possible causal interactions between various biophysical, institutional, and household-level factors. In the irrigated system, despite interventions such as irrigation and agricultural practices like broadcast rice cultivation, these measures, while seemingly supporting farmers' immediate needs, may unintentionally exacerbate drought experiences over time. Specifically, the limited and disproportionate distribution of irrigation resources, combined with behavioral responses to increasing drought events, contributes to a reinforcing feedback loop. As farmers increase investment in new practices which fail to meet their needs (i.e., crop yield) and neglect underlying issues, this leads to declining crop productivity and accumulating financial losses. This, in turn, diminishes households' control over the drought situation and intensifies their perception of drought severity. Although livelihood diversification could lower severity, the reinforcing patterns of perceived drought severity are likely to persist. This underscores the need for future research to explore the long-term effects of these dynamics and for policymakers to develop strategies that not only address immediate needs but also prevent worsening drought conditions over time.

In flood-pulse communities, where fishing is the primary livelihood, the causal loop suggests that delayed recognition of drought's impact on fish harvest, coupled with the pressing stressors like illegal fishing, contributes to lower risk perceptions. This indicates a need for improved awareness and a better connection between environmental changes and their impacts on livelihoods to enhance risk perception and adaptive capacity.

Future research should focus on validating the proposed causal loop diagrams and applying statistical models specific to both fisheries and irrigation systems to better understand these dynamics. We recommend using system dynamics modeling, where information is fed into the hypothesized causal loop diagram. This approach allows for the quantification of behavioral patterns over time and helps identify leverage points for policymakers to mitigate risks. Additionally, statistical models can be employed for sensitivity analysis of the system dynamics model, providing further insights into the robustness of the findings and enhancing the effectiveness of proposed interventions. Extending this work will help clarify the long-term effects of the identified feedback loops and offer a more comprehensive understanding of how these communities perceive and respond to environmental changes, ultimately informing more effective risk communication and adaptation strategies.

CHAPTER III: PERCEIVED PEER EFFECT ON FARMERS' ADAPTIVE BEHAVIORS

1.1 Introduction

Adverse climate-related events raise concerns for agricultural and other natural resource-dependent livelihoods in the developing world (Easterling et al., 2000; IPCC, 2012). This is particularly true for the Lower Mekong Region (LMR), where climate projections suggest an increase in mean temperature of 0.79^{0}C and seasonal rainfall variability, resulting in extreme water flows during wet and dry seasons, intensifying flood, and drought events (Commission, 2010; Eastham et al., 2008). Furthermore, the unprecedented boom in dam construction has triggered rapid hydrological and ecological changes (Pokharel et al., 2018) including novel water, nutrient, and sediment dynamics. These changes affect water and soil quality (Bastakoti et al., 2014; Trung et al., 2020), fish diversity (F. He et al., 2018; Nhung, 2017b) and the livelihoods of agriculture and fisheries dependent populations (Robert, 2017). In particular, small-scale and subsistence farmers in rainfed systems are at substantial risk of water scarcity, reductions in crop yields, increased food prices, and food insecurity risks (IPCC, 2012; MRC, 2019b). Thus, it is imperative to anticipate and respond effectively to minimize farmer vulnerability.

Farmers' decisions (i.e., whether and how) to respond to a changing environment and climate are often referred to as adaptive behaviors (Smit et al., 1999, 2000). In the broad climate change literature, adaptive behaviors include a variety of actions taken by households or communities to reduce the effects of environmental and climate-related changes and can be differentiated by purposefulness (autonomous vs. planned) and timing (proactive vs reactive) (Smit & Pilifosova, 2003). These actions for farmers range from decisions about agricultural management practices (e.g., crop selection, planting time), livelihood strategies (e.g., livelihood diversification) to community-level resilience-building (e.g., seed exchange programs). At the heart of these adaptations is the need for adaptive capacity, which is inextricably linked to the social system in which farmers live and work (Adamson & Bird, 2010) including households and local institutions within their communities. Social systems play a crucial role in supporting farmers' access to and utilization of diverse assets aimed at managing climate risk (Lemos et al., 2016).

Social capital can facilitate building adaptive capacity of natural resource dependent households by providing access to resources (Bebbington, 1999). However, it's the role of social networks—both formal and informal—as embodiments and sources of social capital, that is gaining attention in studies on agricultural innovation (van Rijn et al., 2012), natural resource management (Bodin et al., 2006; Groce et al., 2018; Kramer et al., 2016), resilience, and climate change adaptation (Barnes et al., 2020b; Cassidy & Barnes, 2012; Islam & Walkerden, 2014).

Formal networks such as local government agencies, NGOs, private businesses, and cooperatives play a crucial role in communicating climate risk and awareness, distributing resources, and mediating innovation (Bastakoti et al., 2014). Membership and well-established communication channels often characterize these networks. Whereas informal networks, including peer information exchange and labor networks, rely on personal relationships. While both networks may influence farmer adaptive behaviors, informal networks are particularly important where formal support is absent or limited (Adger, 2003; Cassidy & Barnes, 2012; Tran & Rodela, 2019). In such settings, farmers often rely on informal networks for the exchange of knowledge, labor, or money.

Previous research has analyzed the effects of informal networks on farmer adaptation using measures such as the number of social ties (Wossen et al., 2013), distance to network members, and proportion of network adaptors (Matuschke & Qaim, 2009). These studies, however, do not capture the dynamic process through which farmers interact with and are exposed to the behaviors of their peers over time, leading to changes in their beliefs, knowledge, and behaviors (Barnes et al., 2020b; Frank, 2011). Furthermore, while these studies acknowledge the significance of both formal and informal networks; they analyze their influences independently, limiting our understanding of possible interaction effects. In response to these limitations, we seek to examine the role of farmers' peer and formal networks in influencing adaptive behaviors in response to climate risks in the LMR.

Our central question is whether and to what extent perceptions of peer effect influence farmers' adaptation strategies in response to climate risk. Additionally, we explore how formal networks affect the interplay between perceived peer effect and farmers' adaptive behaviors.

Our study contributes to the existing literature on climate change adaptation in several ways. First, we expand the limited knowledge on how perceived peer effects influence farmers' adaptive behaviors in regions with limited institutional support by quantifying this process through social influence models. Second, we examine how the impact of perceived peer effect varies depending on the presence of ties with formal networks, introducing interaction effects.

Finally, we integrate qualitative methods to validate and extend our quantitative findings, enhancing the robustness of our analysis.

In the following sections, we outline our conceptual framework, describe the materials and methods used, present the results, and discuss their implications, including limitations, and suggest directions for future research.

1.2 Conceptual framework

Our conceptual framework integrates established behavioral theories including bounded rationale and planned behavior (Schlüter et al., 2017), and social influence network theory (Friedkin & Johnsen, 2011) and incorporates empirical findings from climate change adaptation and social network studies (Figure 15).

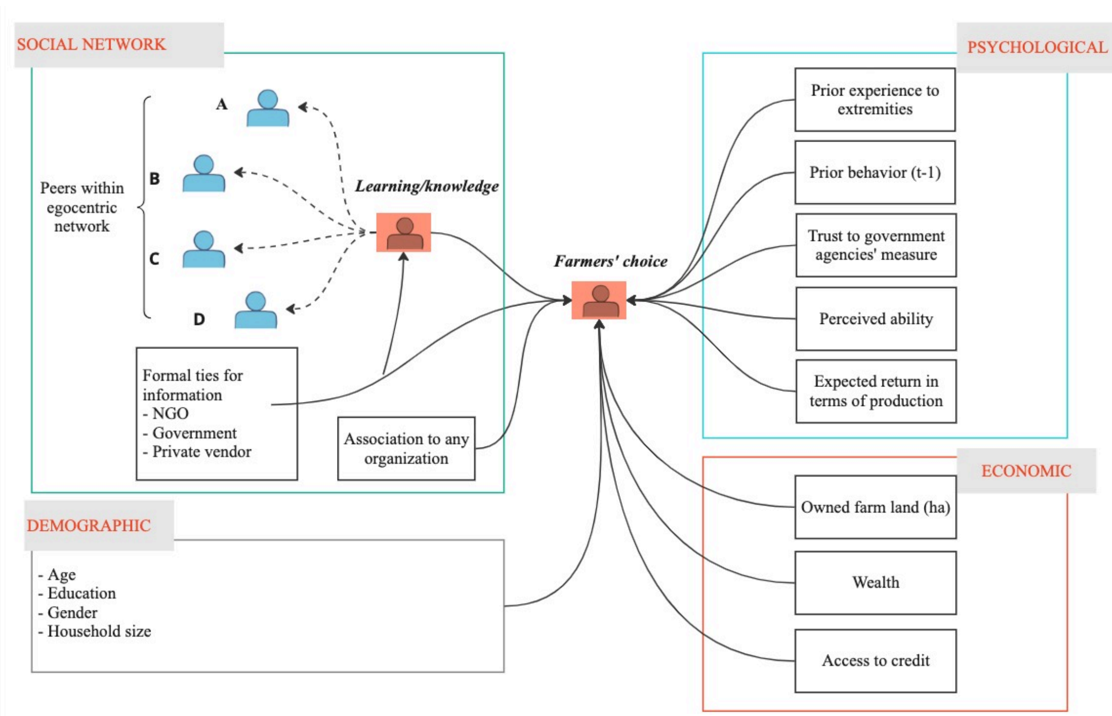


Figure 15: Conceptual framework: Influence of social setworks and other socio-physiological, economic and demographic factors on farmers' adaptation choice

We assume that farmers' decision-making to manage climate risks starts with building knowledge—either through personal experiences or social learning. This knowledge encompasses perceived causes and consequences of climate risks and potential adaptation options. Farmers acquire this knowledge by being exposed to external environments and climate extremes and by attempting various strategies to mitigate risks over time (Ha Vo et al., 2021; Jiao et al., 2020). When farmers' uncertainty is bounded by incomplete information and limited cognitive capacity, they tend to rely on experience and learning from their social networks (Taberna et al., 2023). Social influence network theory describes how individuals update their beliefs and behaviors through interaction and exposure to their peers, including friends and relatives. Additionally, association to formal ties—including NGOs, government agencies, community-based or private organizations—can enhance learning (Arora, 2012) and facilitate adaptation by offering technical and other material support as seen in Thailand (Bastakoti et al., 2014), Vietnam (Bui & Do, 2021) and Ghana (Abdallah et al., 2014).

In making decisions about farm practices, other factors also come into play. Planned behavior theory suggests that behaviors are influenced by behavioral attitudes—shaped by expectation, for example increase in crop yield trust in government bodies management strategies (Cologna & Siegrist, 2020; L. Li et al., 2023) and their perceived ability to manage the risk using appropriate measures, also called perceived adaptive capacity (Grothmann & Patt, 2005). Even if farmers develop adaptation options and intentions, their actual behaviors may be influenced by perceived behavioral controls, that is, their aggregated belief about the control factor (for example, assets) and perceived power of those factors to manage risk.
Economic factors such as wealth, access to credit (Barnes et al., 2020a; Cassidy & Barnes, 2012; Yang-jie et al., 2014) and land tenure security (Abdallah et al., 2014; Jiao et al., 2020; Yaméogo et al., 2018) are the crucial control factors . Further, household characteristics like age (Ha et al., 2023; Ma et al., 2022), education and gender of household head, and household size (Abdallah et al., 2014; Belay & Fekadu, 2021; Ha Vo et al., 2021) can also influence the adaptation decision.

1.3 Materials and methods

1.3.1 Study sites and population

We studied farming households located in the communities near the Tonle Sap Lake in Cambodia (Figure 2). The Tonle Sap, known as the "Great Lake" of Cambodia, is a large freshwater body that, until recently, experienced area fluctuations from 2,500 km² during the dry season to 15,000 km² during the wet season (Matsui et al., 2005; MRC/WUP-FIN, 2007). The lake shares a unique, interconnected hydrological and agricultural ecosystem with the Mekong River via the Tonle Sap River (Keskinen, 2006a) and supports the livelihoods of nearly half of

Cambodia's population (Bonheur, 2001). Although it is well known for its exceptional fish production, the lake's floodplains also significantly contribute to Cambodia's rice production.

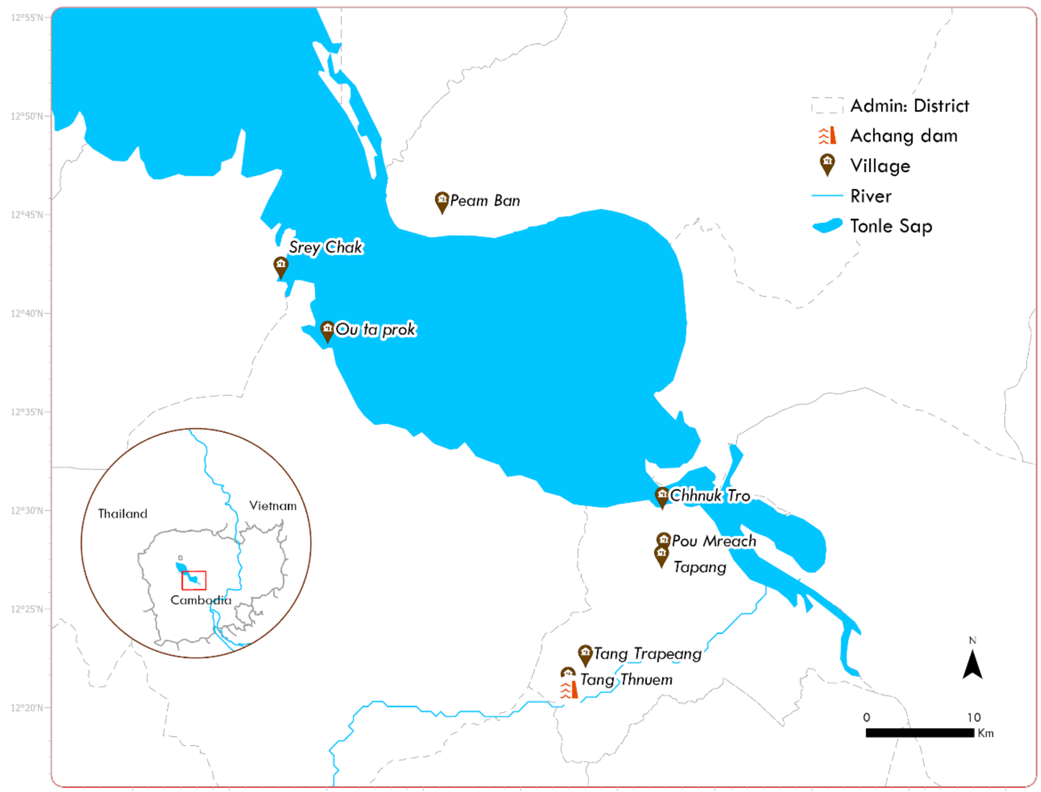


Figure 16: Study communities around the Tonle Sap Lake

The communities around Tonle Sap Lake are part of a socio-economic landscape characterized by diversity in ethnicity (i.e., Khmer, Cham, and Vietnamese), livelihoods, resource access, poverty levels, and vulnerability. The predominant livelihoods are fishing for those living near the lake and rice cultivation for those living farther away. Each is highly susceptible to fluctuations in the lake's flood pulse dynamics (MRC/WUP-FIN, 2007). Other local challenges include rapid population growth, government-led development initiatives like dam construction, and climate change (Nuorteva et al., 2010; Yoshida et al., 2020), heightening the sensitivity of the agricultural sector by extending drought periods, changing flood dynamics, and promoting unjust water governance, which has reduced rice yields (World Bank, 2023), exacerbating indebtedness and food insecurity.

Our sample comprises households from eight villages, purposively selected based on village history interviews with community leaders (January 2023). The selection criteria included 1) proximity to the Achang irrigation dam completed in 2013 and Tonle Sap Lake, 2) proportion of households engaged in farming and fishing, and 3) local livelihood concerns related to current socio-environmental challenges (e.g., land access, farming issues, decline in fisheries, relocation, migration) and a diverse set of responses to those issues in communities.

Four communities, Chhnuk Tru, Ou Ta Prok, Peam Bang, and Srey Chak, are located on the floodplain of Tonle Sap Lake. Residents of these communities typically engage in fishing during the wet season (June- October), farming during the dry season (November-May) and seasonal wage labor activities. The other four villages, Tang Thnuem, Tang Trapeang, Tapang, and Pou Mreach, are located at different distances downstream of the Achang irrigation dam and within 15 km of Tonle Sap Lake and primarily comprise rice farmers.

We considered households mainly engaged in rice production as the primary unit of analysis and therefore included 213 of 400 households sampled from eight communities. We then identified and excluded cases with missing survey responses, resulting in a final sample size of 198 households.

1.3.2 Data collection

We collected data using household surveys, informal in-depth interviews, and participatory observation methods between May 2022 and June 2022 using the tablet-based Open Data Kit platform (ODK) (Hartung et al., 2010). Our study is approved by Institutional Review Board (IRB) of Michigan State University under the reference number STUDY00004770. We obtained oral consent from all participants prior the start of the study. The consent form, detailing the study's purpose, data usage, confidentiality measures, and the right to refuse participation, was explained to all participants prior to obtaining their approval.

A trained, Cambodian research team conducted 90 minutes face-to-face surveys with household heads. They used a pretested structured and semi-structured questionnaire to collect cross-sectional and retrospective information on household demographics, income and debt, material wealth, food security, drought, social networks and relations, resilience, and livelihoods including detailed information on farming, fishing, and aquaculture. Following the survey, the Cambodian and MSU teams conducted informal interviews with local villagers in six communities near the Achang irrigation dam to understand recent farm-related challenges including rice cropping practices, infrastructure development, climate change, coping and adaptation strategies, and local support.

Network Data Collection

Definitions Using theoretical frameworks and empirical results from recent scholarship on social network analysis and climate change adaptation (Barnes et al., 2020b; Matuschke & Qaim, 2009), we define a social network as a source of social capital that facilitates adaptation to environmental and climate change through the exchange of resources, knowledge, practices, and norms within interconnected ecological and social systems. We focus on social ties among farmers in informal peer or ego-centric networks (i.e., friends, family members, or neighbors) centered on an individual farmer (i.e., the 'ego') for information exchange. Furthermore, we considered three formal networks including non-governmental organizations (NGOs), government agencies, and private vendors, representing more structured relationships that can also facilitate adaptation in a rural, agricultural context (Adger, 2003).

Methods Given the challenges associated with conventional network data collection methods, we adopted an alternative approach better suited to our study context. Previous studies have used methods such as the 'name-generator technique' (Isaac, 2012; Isaac et al., 2014), the 'first-name-cue method' (Matouš et al., 2013), and snowball methods (Albizua et al., 2021) to collect network data. These methods presented challenges in our study context. First, these approaches require the names of individuals from whom the surveyed farmers seek information, followed by interviewing those listed individuals. However, in our study communities, residents use nicknames instead of formal names, posing difficulties in accurately identifying peers. Second, these methods require collecting network data from all nominated individuals within a defined village boundary. However, in many agricultural systems, including rural Cambodia, farmers rely on close ego networks and connections beyond village boundaries (Bandiera & Rasul, 2006; Conley & Udry, 2001) as indicated in our village histories.

Instead, we collected complete egocentric network data from each sampled household. Each household head noted up to five people from whom they seek information and advice about farming. We refer to these individuals as informal network partners. This approach has been shown to provide reliable information on individuals with whom respondents interact regularly (Marsden 2011, pp. 382-383). For each network partner, household heads were asked to provide information about their network partners including location, the nature of their relationship, and frequency of interactions. They were also asked to report whether their network partners made behavioral changes recently regarding crop selection and farm management (i.e., intercropping, irrigation, fertilizers, and pesticides). Ma *et al.* (2022) applied a similar approach to collect information on climate change behavior on the relatives, friends, neighbors, and government of respondents in China.

This approach has some limitations. Most obviously, we did not obtain first-hand information from network partners. However, social learning theory and previous studies suggest that while farmers may not have detailed knowledge about other farmers' practices (e.g., amount of fertilizer or pesticide applied), they do have general information of their peers' practices through interaction and/or observation (Conley & Udry, 2001), providing reliable information on adaptive practices within egocentric networks of farmers.

Lastly, we also collected information on formal network sources from which households obtain information and advice on farming.

Measures of peer effect We used perceived peer effect (PPE) as the measure of the informal peer network effect, which combines the perceived frequency of interactions and the adaptive behaviors of those peers within respondents' egocentric networks. This concept is grounded in the discussion of dynamic interactions within social networks (Manski, 2000) and influence modeling for natural resource management (Frank, 2011). Both highlight that individuals' behaviors are influenced by their network with a time lag, as they interact, observe, and gradually adopt the behaviors of their peers. Also, prior studies identify the role of social networks and network partners' behaviors on adaptation (Matuschke & Qaim, 2009; Moritz et al., 2024; Wossen et al., 2013). By considering both the frequency of interactions over 12 months and the adaptive behaviors of peers, our measure captures the gradual process through which peer influence affects farm activities in their networks.

We use "perceived peer effect," an adapted version of the term "network exposure" used by previous scholars in social influence models (Barnes et al., 2020b; Frank, 2011), because it captures the farmer respondents' self-reported ties, levels of interaction, and adaptive behaviors of their peers. While this measure is less common in social network and climate change studies, its use is growing in social network studies in the fields like education, particularly in examining risk behaviors and substance use among adolescents and young adults (Hofer et al., 2024; Schuler et al., 2019). Studies have even found that perceived peer behaviors can have a greater influence than actual peer behaviors in shaping individual decisions (Watts et al., 2024).

This focus on perception is critical because, as research in agriculture shows, farmers' perceptions of what their peers are doing or expect them to do can be as important as actual behaviors. For instance, Vasquez *et al.* (2019) found that perceived norms around antimicrobial use influenced farmers' intentions on New York dairy farms. Similarly, Qiu, Zhong and Huang (2021) showed that perceived peer behavior affected decisions on land protection in China. Qiao *et al.* (2022) also observed that perceived peer behavior (as they use farmers' self-reported behavior of their surrounding farmers) influence farmers' decisions on green production. These findings underscore that perceptions of peer behavior can be influential in decision-making processes.

1.3.3 Covariate selection

Initially, we considered 18 covariates suggested by behavioral theories and a review of empirical studies explaining adaptive behaviors to climate change (see Figure 15). To account for the explanatory power and sensitivity of the Poisson model given our sample size of 198, we employed a multimodal inference approach using the MuMIn package in R (Bartoń, 2024) to further identify key covariates. From this process, we identified 12 covariates which included our variables of interest (i.e., perceived peer effect and the interaction of perceived peer effect with formal ties), that appeared significant across the top 20 models with high predictive power based on AIC and holds high weights in the relative importance analysis. For consistency and to examine the robustness of results, we applied the same covariates in our Probit model. We performed a power analysis to confirm the appropriateness of the selected number of variables for each model (Pseudo R^2 = 0.1-3, power = 0.84-0.99, at *p-value* = 0.05).

Measures of selected covariates

We considered three types of formal networks, ties to government bodies, NGOs, and private vendors, coded as dummy variables with binary responses where '1' denotes the presence ('Yes') and '0' the absence ('No') of the respective ties.

We used two measures of economic condition: amount of land owned in hectares ('land ownership') and a wealth index derived from principal component analysis (PCA) (Córdova, 2008; Howe et al., 2008) using proxy measures (total number of durable assets owned by the household, access to improved source of drinking water, improved source of fuel for cooking and lightening, improved toilet facilities, the amount of land owned (ha) and Total Livestock Unit (TLU)). We used change in crop productivity compared to past few years as a proxy measure of farmers' expected return from adaptive behavior, coded as dummy variable where '1' denotes decrease in crop productivity and '0' denotes same or increase in crop productivity. We also included the total number of extreme events faced by farming households ('multiple shocks') as a measure of psychological factor. Further, we controlled for the household head's age. Table 9 provides summary statistics for model covariates and expected associations.

Table 9: Summary statistics for the model covariates

Variables		Frequency	Mean	Std. Dev.	Min	Max	Expected sign
Perceived peer effect	PPE-intensity		5	4.37	0	20	+
	PPE- irrigation use		4.06	1.87	1	8	+
	PPE- fertilizer use		5.30	2.30	1	8	+
	PPE - pesticide use		5.10	2.29	1	8	+
Formal network effect	Ties- government				0	1	±
	Yes =1	15.2%					
	No =0	84.8%					
	Ties- NGO				0	1	±
	Yes =1	23.2%					
	No =0	76.8%					
	Ties- private				0	1	±
	Yes =1	14.1%					
	No =0	85.9%					
Psychological	previous experience to multiple shocks		2.25	0.89	0	3	+
	crop productivity				0	1	–
	Decreased =1	49 %					
	Increased/ same=0	51 %					
Economic	land ownership (ha)		1.3	1.1	0.1	10	+
	wealth index		-0.03	1.2	-2.37	3.67	+
Demographic	Age (Yrs)		48.18	12.62	22	86	±

1.3.4 Analytical approach

We adopted a mixed-method approach, integrating both statistical methods and qualitative approaches for data collection and analysis.

a. Quantitative

We used network influence models to measure and understand how farmers' behaviors are affected by perception of peer behaviors within their egocentric networks (Bodin et al., 2006). Influence models have been used to examine the network effect on fisher's decisions to enforce rules of sea tenure (Stevens et al., 2015), hunters' harvest decision (Kramer et al., 2016); and households' adaptive and transformative actions related to climate change (Barnes et al., 2020b).

We applied a two-step modelling approach. First, we analyzed the influence of a farmers' formal and informal social networks on the *extent* of adoption of adaptive behaviors (i.e., adaptation intensity) or the total count of all adaptation behaviors adopted. We also modeled the effect of networks on farmers' specific adaptive behaviors (i.e., adaptation choices) such as crop and farm management.

To determine whether there was any clustering effect and need for hierarchical linear modeling approach, we conducted a random effects ANOVA analysis at a significance level 5%, followed by computing the interclass correlation coefficient (ICC) value (Snijders & Bosker, 2011; Steenbergen & Jones, 2002). The ANOVA results suggested no significant variability in adaptation intensity across communities. Further, an ICC value of 0.02 indicated only 2% of variance in adaptation intensity is accounted for at the village level (Hedges & Hedberg, 2007). These results suggest no clustering effect; thus, our modeling accounts for only household-level factors.

Social Network and Adaptation Intensity

Adaptation intensity represents the cumulative count of nine adaptive behaviors adopted by each farmer. We identified these behaviors through cross-tabulation, utilizing the significance of Pearson Chi-square ($p < 0.05$) and Cramer's coefficient (Φc), with a focus on significant moderate to strong associations ($0.3 > \Phi c > 0.5$) (Cohen, 1988). This approach ensures that the included behaviors are not just random or coincidental, resulting in index values that accurately reflect farmers' adaptive behaviors. It is important to note that this measure captures only the diversity of adaptation actions, which may not directly indicate the intensity of resource investment or commitment to each practices. Although this framing is consistent with prior research (Jiao et al., 2020; N. A. Khan et al., 2021), we acknowledge it as a study limitation, as the number of adaptations may not fully represent the true intensity or sustainability of the adaptation efforts.

Further, we did not assess the adaptive behaviors of farmers in terms of their usefulness, sustainability, or whether they were positive or negative. Instead, our focus was on documenting the range of adaptive practices employed by farmers in response to climate challenges, without making normative judgments about which adaptations are preferable or more effective in the long term.

Because adaptation intensity followed a Poisson distribution with a dispersion parameter (δ) of 1, we used the basic Poisson model for our analysis (Hoffmann, 2016), which is well suited to situations when the mean is equal to the variance, as was the case with our data.

Assuming that a farmer *i* made p^{th} changes in his/her farm management practices over the past few years ($t - t_1$), we mathematically express this as

$$ln(\lambda_{i(t-t_1)}) = \beta_0 + \sum_{p=1}^{p} \beta_p x_{pi} + e_i \qquad (1)$$

In the model, $ln(\lambda_{i(t-t_1)})$ is the natural logarithm of the mean rate parameter for the Poisson distribution corresponding to the adaptation intensity for the i^{th} farmer (i= 1,…,n) over the period (t-t_1). In our study, we interpret λ as the average extent of adaptation by a farmer. β_0 is the intercept term, x_{pi} (p = 1, 2, . . ., p) denotes household level covariates (Table 1), β_p are the coefficients associated with covariates, and $e_i \sim N(0, \sigma_e^2)$ is the error term.

Expanding equation 1 in terms of social network analysis using an influence model as guided by Friedkin and Johnsen (2011) and Frank, (2011),

$$\ln(\lambda_{i(t-t_1)}) = \beta_0 + \beta_1 \sum_{i'=1}^{n} w_{ii'(t-1)-t} Y_{behaviori'(t-1)} \;/\; \sum_{i'}^{n} x_{ii'} + \sum_{p=1}^{p} \beta_p x_{pi} + e_i \quad (2)$$

In the model, farmer i, interacting with his/her egocentric network partner i' in last 12 months, denoted as $w_{ii'(t-1)-t}$. $Y_{behaviori'(t-1)}$ is the total number of farm related changes made by network partner i'. $x_{ii'}$ is the total number of partners in their ego-centric network. Then, $\sum_{i'=1}^{n} w_{ii'(t-1)-t} Y_{behaviori'(t-1)} \;/\; \sum_{i'}^{n} x_{ii'}$ is the egocentric network effect (PPE), which represents the farmers' perceived exposure to the practices in one's network via interaction over time, explained by β_1.

We used Maximum Likelihood Estimation (MLE) to estimate regression coefficients in the Poisson model. MLE, well suited for count data, allows for precise estimation of intercept (β_0), and covariate coefficients (β_p) in Equation (2)'s network analysis expansion. This optimization aligns our parameter estimates with data distribution, enhancing analysis validity and reliability. Further, we calculated incident rate ratio (IRR), derived from the exponentiation of β, to explain the multiplicative effect of covariates on adaptation intensity. To enhance interpretability, we reported the IRR value as a percentage, calculated as (IRR-1) multiplied by 100. We used robust standard errors for the estimates to address heteroscedasticity.

Social Network and Adaptation Choices

We employed a probit model to analyze the influence of egocentric networks on farmers' adaption choices (i.e., increases in fertilizer, pesticide, and irrigation), specified as follows:

$$y_{ij(t-t_1))}= \beta_0+ \beta_1 \sum_{i'=1}^{n} w_{ii'(t-1)-t} Y_{behaviori'(t-1)} / \sum_{i'}^{n} x_{ii'} + \sum_{p=1}^{p} \beta_p x_{pi} + e_i \quad (3)$$

where $y_{ij(t\text{-}t1)}$ (j=1, …, n) denotes changes in one of three practices by i^{th} farmer (i=1,…, n) during period (t-t_1). The interaction term $\sum_{i'=1}^{n} w_{ii'(t-1)-t} Y_{behaviori'(t-1)} / \sum_{i'}^{n} x_{ii'}$ represents the exposure within the last 12 months to partners making the same change as reported by farmers. β_1 explains the effect of ego-centric networks on farmers' binary choices. We used three measures of perceived peer effect specific to each choice, including 'PPE- irrigation use', 'PPE- pesticide use' and 'PPE- fertilizer use' in the models. We reported the Average Marginal Effects (AME) to explain the association between covariates and the likelihood of a farmer's binary decision, presented as a percentage.

In our models, we tested an interaction term to understand the impact of informal networks on adaptive behaviors among farmers in the presence or absence of ties with formal networks. Given the potential for inappropriate and misleading interpretations of interaction term coefficients in nonlinear models (Berry et al., 2010), we used marginal effects and tests of second differences (AME) to determine the presence and nature of the interaction effect (Mize, 2019). This approach allowed us to define interaction as the change in the marginal effect of an informal network on adaptive behaviors in the presence or absence of formal network ties (McCabe et al., 2022), providing an intuitive understanding of the interaction dynamics.

b. Qualitative

We adopted a thematic approach for coding qualitative data, following recommended thematic analysis procedures (Miles et al., 2014), to extract and label meaningful themes (i.e., code) and concepts from responses to semi-structured questions. The Cambodian research team transcribed (Khmer) and translated (English) all recorded qualitative responses from audio files (3700) beginning with a subset of 20% of files. Both the Cambodian and Michigan State University (MSU) teams then identified themes and concepts resulting in codes, which were then applied to the subset of audio files to validate code applicability. Over three rounds of collective discussion, iterative coding adjustments, and determinations of high inter-coder reliability, a final set of codes, specified to each open-ended question, were developed, and applied to all qualitative responses.

We developed summary statements from qualitative data collected using informal interviews by extracting key sentences or paragraphs corresponding to each code. These statements served as anecdotes, suggesting underlying reasons or mechanisms for behaviors noted by participants.

1.4 Results

1.4.1 Behavioral changes

Sampled households primarily cultivate rice for household consumption (~85%) with different varieties used depending on local topography and elevations, for example, long rice in the low flatlands (~80%), medium rice at medium altitudes (7%) and short-term rice in upland areas (27%). These varieties have distinct maturation periods after sowing (MDS) (Poulton et al., 2016). Households' choice of rice varieties depends on the availability of irrigation to which only 40 percent of households have access and used mostly during the wet season (62.8%) and less during dry season (12.8%).

Households experienced multiple shocks to their farms, ranking drought first (96%) followed by pests (46%), increasing food prices (33%), and floods and storms (24%). Households made changes to their farm management practices in response (Figure 17) including planting time (65%) and the use of fertilizers (58%), insecticides (46%), new farm equipment (28%), and irrigation (12%). Fewer households made land and water management related adjustments including increases in land area, burn practices, and use of water efficient methods and intercropping.

On average, farm households adopted approximately two behaviors each while the extent of adaptation, measured by the adaptation intensity index, varied between one and seven. Many farmers reported increased use of fertilizers and pesticides as well as changes in planting time following their transition from labor-intensive, conventional rice transplantation to mechanized, broadcast techniques. Nearly 46 percent of respondents reported the change in the rice plantation method as the primary reason for these farming-related changes (See APPENDIX C Table 13 for details).

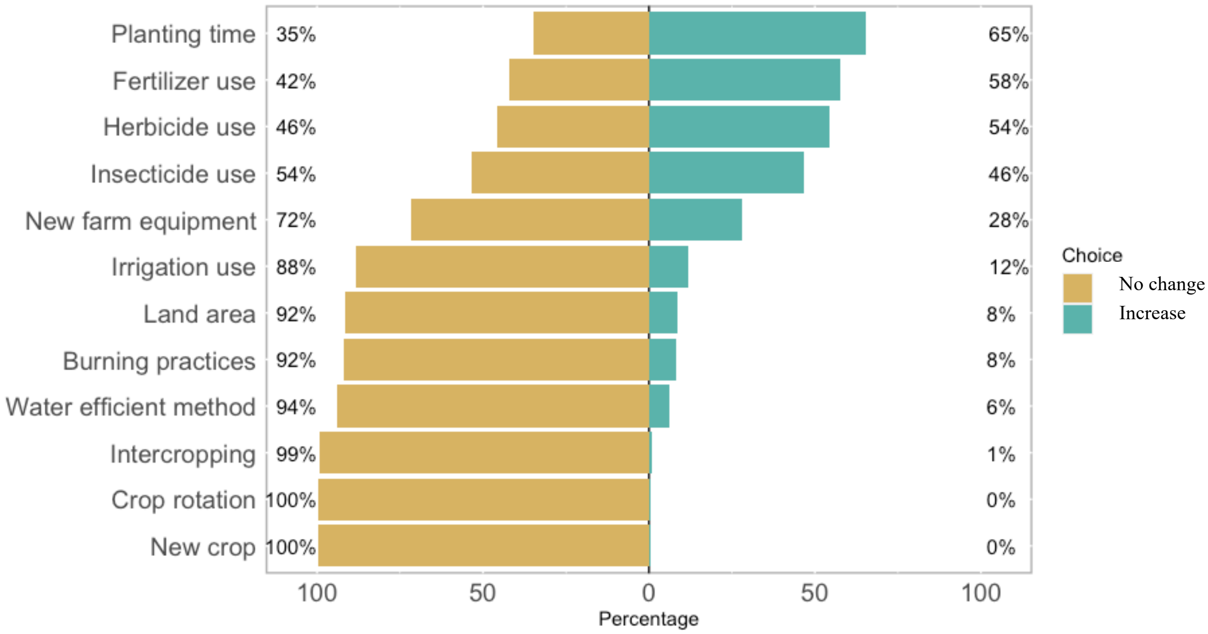


Figure 17: Households' changes in farm practices

In interviews, farmers reported that this shift has led them to invest more in agricultural inputs as they faced increasing weed problems and decreasing rice yield. One farmer expressed this sentiment by stating,

> *"Now I use more fertilizer than in the past. If I don't use more fertilizer, I don't get good yield. And if we grow the rice by broadcasting the rice, it needs more fertilizer. If not, we don't have (good) yield. I also use more weedicide than before because we broadcast the rice and then, we have more weeds. If we transplant the rice, we have fewer weeds."* (Male, Tang Thnuem)

Many farmers (52 %) reported increased pesticide usage in response to heightened pest and weed problems, while 47 % reported increased fertilizer use due to declines in soil fertility (APPENDIX C Table 14). Despite these adjustments, many farmers interviewed admitted experiencing lower yields thereby heightening their expenses. However, they expressed a strong preference to persist with these changes to maintain yields and livelihoods in the face of more frequent droughts.

"When I shifted from long term to short term rice, I got less yield. Because of drought, I lost crops, but I think it is better to practice short term (rice) as I can assure the yield at least, though it is less." (Female, Khum Ponley)

1.4.2 Social network

In the previous year, farmers have, on average, used 1.64 distinct sources (ranging from 1 to 10) for farming-related information. Not surprisingly, a majority use informal peers (69.6%) including household members within and outside the home as well as friends and neighbors. Fewer households (36.3 %) maintain links with formal networks (i.e., NGOs, government officials, private vendors). Interview responses suggest that households with farmland close to the irrigation canal are more likely to receive support from NGOs including training, technology assistance, access to credit, and sales opportunities. In contrast, households without NGO support more often rely on their neighbors, relatives, and local vendors.

Farmers identified between one and four individuals in their informal or egocentric network from whom they receive information and advice regarding farming including household members living outside the home (41.75%), friends and relatives (28.07%), and household members (21.05%). Informal network partners were geographically dispersed with ties both within and outside the community and commune (Figure 18).

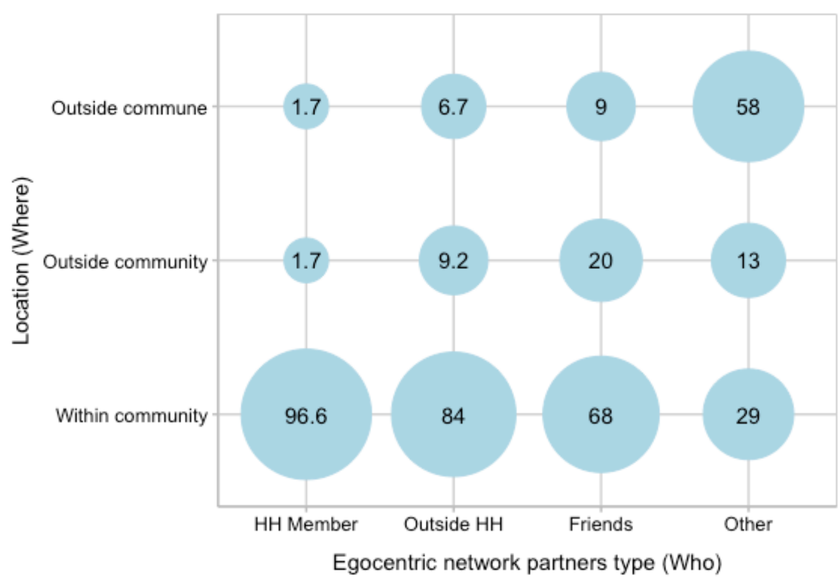


Figure 18: The spatial distribution of farm households' network partners (value in percentage)

[Note: 'HH Member' refers to the household members living within the home and 'Outside HH' refers to the household members living outside the home. The Commune is the third-level administrative division in Cambodia after province and district and includes villages.]

Interview responses suggest that farmers do not make farming-related decisions in social isolation. Instead, they rely on their peer networks decision as reflected in response:

> "*We individually cannot decide which crop variety to grow. We depend on our neighbors. Whatever variety they choose. The harvest period should comply with other farmers in the village; otherwise, we could not carry the harvest together with others and sell it in the market*." (Female, Pech Changvar)

Some farmers described how they follow the practices of their neighbors, as one farmer expressed, " *I did not have reason to make changes, but I observed in my community that people made changes in crop varieties, and I followed them*" (Woman, Tang Thnum). Others mentioned learning through observation about practices like short-term rice plantation and planting time, as echoed in responses:

> *I saw farmers planting rice two times in the land nearby canal. I realized that if I continue practicing long-term rice plantation, then with uncertainty in rainfall, I will get less rice yield.*" (Female, Khum Ponley)
>
> "*We observe how our neighbors grow and plant rice and their yield and if it is good, then we ask them if they can exchange their variety. Sometimes we exchange seeds, and some buy from them. We also discussed methods. The short-term rice plantation takes 3 months and long-term takes 6 months. We discuss and agree... someone use one long term and one two times short term variety so that we could match total duration and the harvest month.*" (Female, Pech Changvar)

1.4.3 Social network and adaptation intensity

Results from the Poisson model, presented in Figure 19, indicate a significant positive relationship of perceived peer effects on farmers' adaptation intensity. The IRR value suggests that with each one-unit increase in farmers' perceived exposure to their network partners' behaviors, adaptation intensity rises by 5.5 percent (IRR=1.055, *p-value* <0.001).

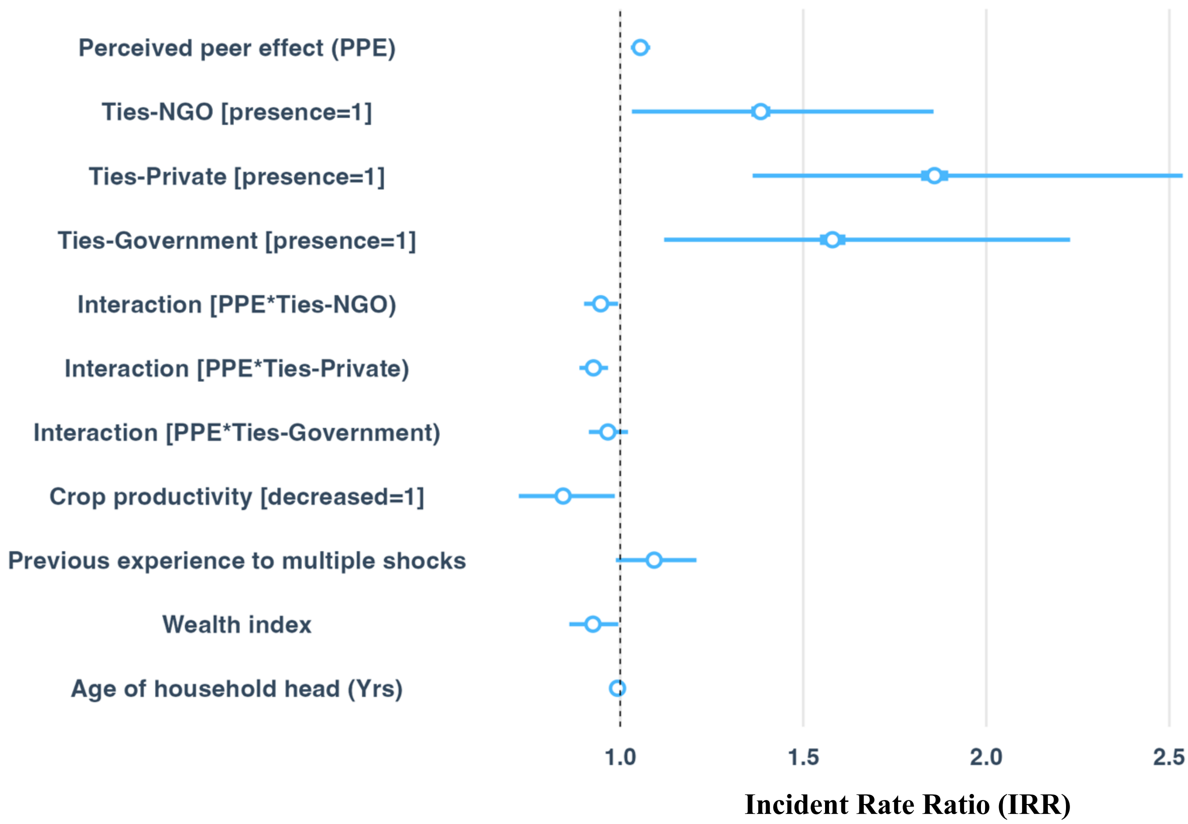


Figure 19:Poisson model results

We found a significant association between the farmers' adaptation intensity and their ties to formal networks, suggesting that connections to NGOs, government, and private vendors considerably increases the likelihood of farmers' adopting adaptation behaviors. Comparing all formal networks, we found ties with private vendors exert the largest influence on adaptation intensity, increasing adaptation intensity by 85.8 percent compared to those with no such ties (IRR = 1.858, *p-value* <0.001). This contrasts with a 57.9 percent increase associated with government ties (IRR = 1.579, *p-value* <0.01) and 38.4 percent increase with ties to NGOs (IRR=1.384, *p-value* < 0.05).

Assessing the interactive effects of peer and formal networks on adaptation intensity, our results reveal a significant positive perceived peer effects among farmers without formal network ties (APPENDIX D Table 16). This difference is more pronounced among farmers with and without private vendor ties (25.7 percentage points higher for those without ties, second difference in AME= 0.257 value, p-value <0.01), followed by farmers with and without NGO ties (16.2 percentage points higher for those without ties, second difference in AME= 0.162 value, p-value <0.1) (Figure 20a & Figure 20b). Interactions with government networks do not show any effect (second difference in AME= 0.105 value, p-value > 0.1), suggesting that government ties do not change relationship between perceived peer effect and adaptation intensity (Figure 20c).

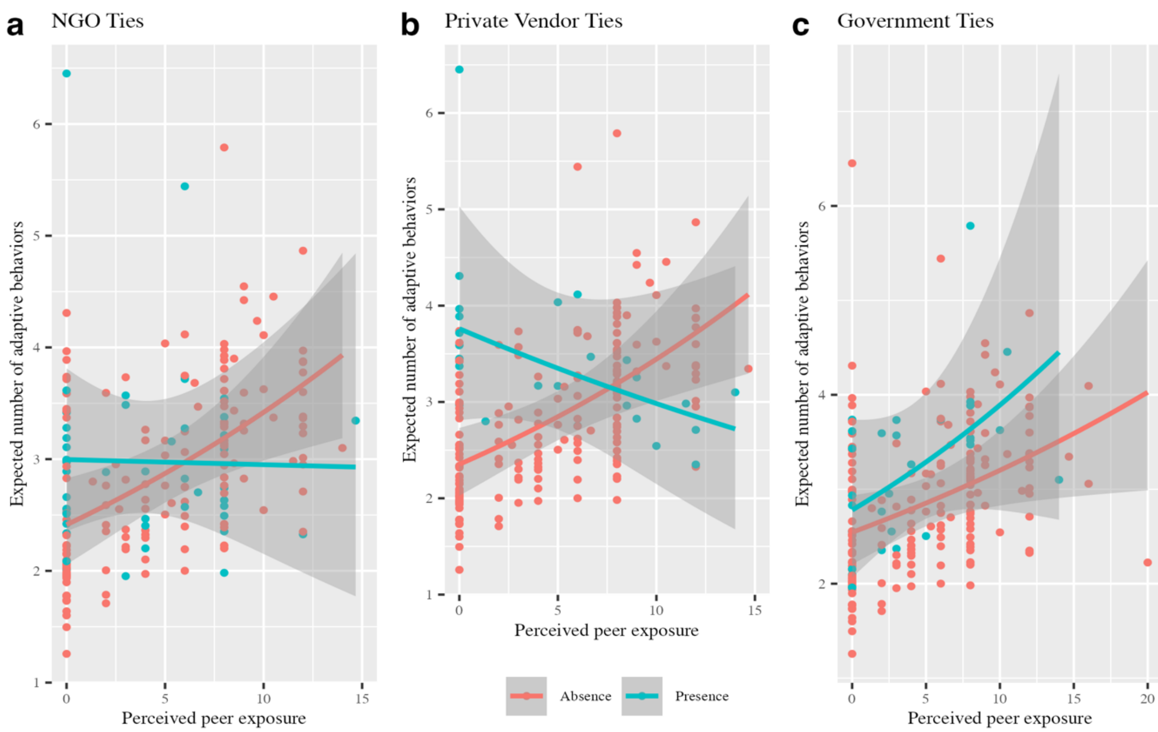


Figure 20: Probability of adopting multiple adaptive behaviors depending on the perceived peer exposure and one's ties to formal networks

Looking at other control factors, farmers' previous experience with multiple shocks, as expected, increases adaptation intensity by 9.3 percent for each additional climate shock (IRR = 1.093, *p-value* <0.1). Alternatively, wealthier households have lower adaptation intensities, a decrease of 7.5 percent for each additional unit increase in household wealth (IRR=0.925, *p-value* <0.1). As expected, farmers experiencing a decrease in crop productivity are less likely to intensify adaptive measures, around 15 percent lower compared to those experiencing an increase or no change in crop productivity. Further, as the household head ages, there may be a modest decline (0.7%) in the propensity to adopt multiple adaptive measures (IRR = 0.993, *p-value* <0.05). Contrary to previous studies, our analysis revealed no significant effects of land ownership on adaptation intensity.

1.4.4 Social network and adaptation choices

Figure a presents the probit model results for distinct adaptation choices (i.e., increase in irrigation, pesticide, and fertilizer use) excluding interaction term (APPENDIX D Table 15 for details).

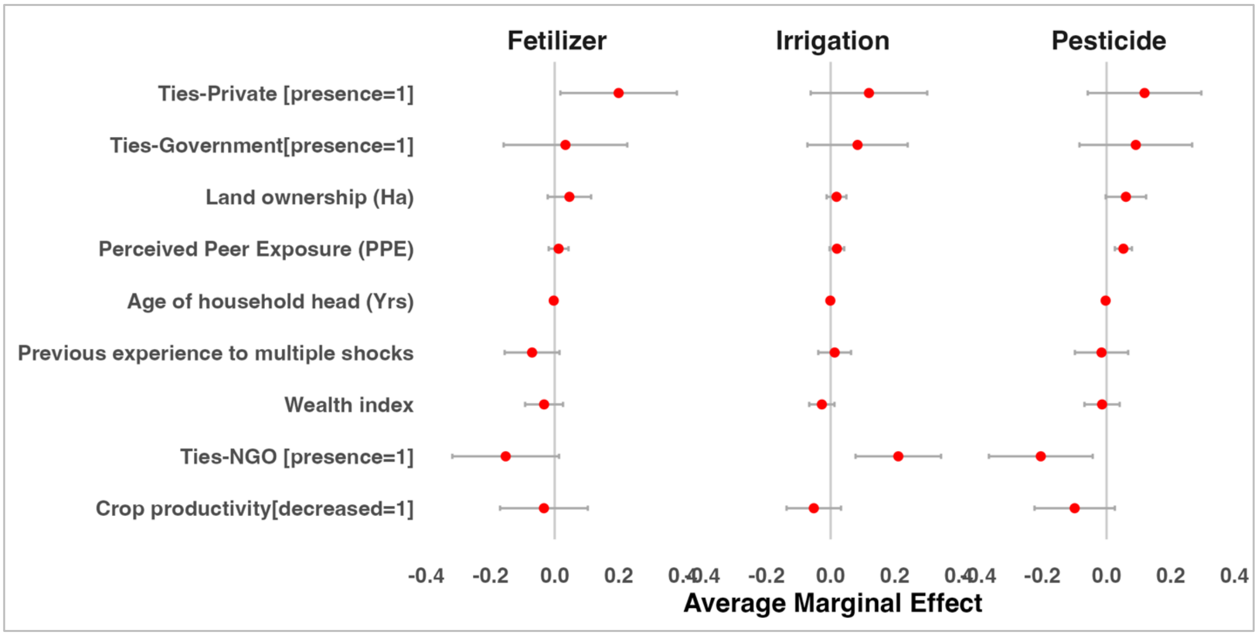


Figure 21: Probit model results: Main effects of variables (Average Marginal Effects)

Unlike perceived peer effect on adaptation intensity, peer networks did not affect farmers' decisions to increase irrigation and fertilizer use. However, peer networks positively influenced the likelihood of increasing pesticide use by 5.2 percent (AME =0.052, *p-value* <0.001).

Ties to NGOs significantly influenced farmers' behaviors concerning irrigation, pesticide and fertilizer use, albeit differently. The likelihood of farmers intensifying irrigation use increased by around 21 percent among households with ties to NGOs (AME= 0.211, p-value <0.01). Conversely, households' ties to NGOs are associated with a decreased likelihood of intensifying pesticide use by 20 percent (AME= 0.205, p-value <0.05) and fertilizer use by 15 percent (AME = -0.153, p-value <0.1) compared to those without it. Ties with private vendors positively affected the decision to increase fertilizer use (AME = 0.199, p-value <0.05). Finally, ties to government agencies did not affect any farmer adaptation choices.

Consistent with the findings of the adaptation intensity model, our adaptation choice model showed significant interaction effects, specifically formal ties with NGOs and private vendors. Ties with NGOs appeared to moderate the perceived peer effect, reducing the likelihood of using pesticides and fertilizer use by around 10 and 7 percentage points, respectively (Figure 22b and Figure 22c). On the contrary, NGO ties positively influenced perceived peer effect on irrigation practices by 5.7 percentage points higher compared to those without such ties (Figure 22a, and APPENDIX D Table 17).

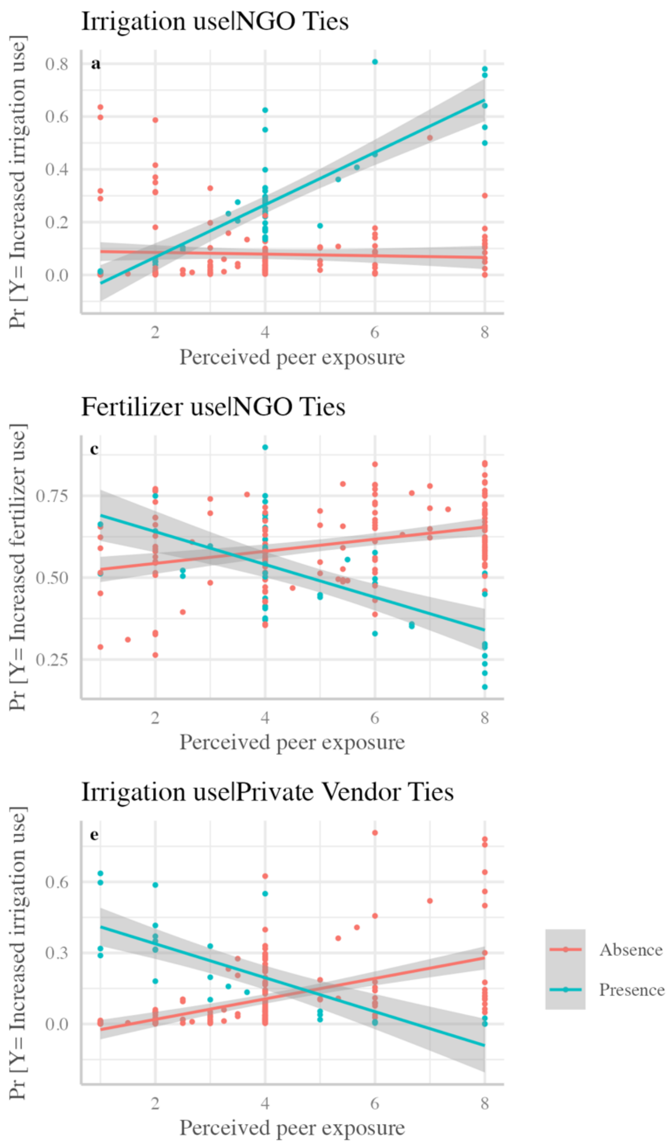


Figure 22: Probability of taking a particular adaptive behavior depending on the peer network exposure and one's tie to formal networks

Private vendor ties, similar to NGO ties, moderate the perceived peer effect leading to a decrease in pesticide use among households with such connections (Figure 22d) and unlike the effect of NGO ties, households with private vendor ties decrease the likelihood of adopting irrigation practices by around 14 percent (Figure 22e).

In addition to network effects, land ownership was a significant factor influencing farmers' adaptation behaviors, particularly in increasing pesticide use such that for each additional hectare, households increased their pesticide use by 6 percent. Unlike the effects on adaptation intensity, our analysis did not find any significant effect of previous experience to multiple shocks, change in crop productivity, wealth index and age of household head on farmers' adaptation choices.

1.5 Discussion

Rice farming households across communities undertook a variety of incremental adaptation behaviors, either singly or in combination, including increased use of fertilizers, herbicides, and insecticides, and adjustment in planting times (Dapilah & Nielsen, 2020). These adaptations are not isolated responses but are intertwined within the broader transformation of rice farming systems. This transformation is characterized by a shift from conventional labor-intensive planting methods to mechanized broadcast techniques in the context of increasing climate events, mainly drought and water infrastructure developments like irrigation systems (APPENDIX B Table 13), as evident in other parts of Cambodia (W. N. Green, 2020).

In addition to institutional arrangements and climate change, we found evidence that household-level factors, including social networks significantly shape the adaptive behaviors of farmers. Most farmers seek farming-related information and advice from their informal peer networks. Adger characterizes peer networks as a form of bonding capital, operating within a community, and thriving in contexts marked by limited or absent governmental support (Adger, 2003). While some connect to formal networks, for example, NGOs, for training, technological assistance, credit, and marketing services, this is limited to few households, depending on farm location and their contribution to rice farm production.

Our findings suggest the importance of peer networks in influencing farmers' adaptive behaviors, explained by perceived peer effect. This finding suggests a dynamic behavioral pattern: As farmers increasingly interact with their personal network partners, these relationships become a conduit for sharing knowledge and experiences about practices and outcomes. Over time, these exchanges may shape their beliefs and behaviors, culminating in the adoption of farm practices. This pattern is corroborated by narratives from interviews. Local farmers frequently reported observing and interacting with their close neighbors and adopting their practices on rice variety selection and planting times as seen similarly in other agricultural contexts. In experimental study in Uzbekistan, Moritz *et al.* (2024) found that observational learning within small, close peer groups significantly influenced farmers' adaptation choices regarding Index Insurance and Savings. Additionally, the lagged innovation choices of neighbors continued to shape farmers' behaviors in subsequent seasons. Similarly, Ma *et al.* (2022) observed a significant positive effect of adaptive behaviors among relatives, friends, and neighbors on farmers' responses to climate change in China. This pattern is also evident among pineapple farmers in Ghana (Conley & Udry, 2001) and hybrid seed adopting farmers in India (Matuschke & Qaim, 2009).

Looking at the perceived peer effect on a particular behavior, we find a significant association limited to pesticide use. One explanation is farmers' higher perceived urgency in addressing weed and pest-related challenges. As most farmers faced pest problems, pesticide use could be widely discussed and promoted within social networks. Also, farmers with limited resources are more likely to embrace practices that provide immediate feedback and noticeable impact in terms of preventing large production losses (Chèze et al., 2020).

Our results showed varying perceived peer effect on adaptive behaviors in the presence or absence of formal network ties, particularly NGOs and private vendors. Households with such ties tend to reduce their adaptive behaviors as they perceive increasing exposure to their informal peers' behaviors. Matouš *et al. (*2013) observed similar result in their study of Ethiopian farmers who become less receptive to information and conservation practices from extension agents as the proportion of communal ties in their network grows.

NGO interaction effects differ by behavior type. Ties with NGO for farming-related information synergizes the effect of peer influence on the use of irrigation. As indicated in interview responses, NGOs actively engage with these farmers by providing valuable training, providing credit support, and assisting with marketing services. This engagement seems to encourage these farmers to invest more in irrigation practices, potentially increasing crop yields amidst escalating drought severity. NGOs also provide support in marketing and selling farm products, helping farmers repay loans and safeguard livelihoods. However, farmers with NGO ties are less likely to increase fertilizer and pesticide usage compared to those without ties, perhaps attributable to NGOs' focus on promoting sustainable practices. Locals reported receiving training in the use and timing of fertilizer and pesticides.

These observations suggest nuanced effects between formal and informal networks on adaptation choices and intensity. However, these networks may have distinct roles in various stages of adaptation, especially in contexts where institutional support is limited. Interview responses indicate that NGOs provide knowledge on practices such as broadcast planting, crop varieties, application of fertilizers and pesticides through a small number of local community members. As farmers who received support begin to realize benefits, other farmers with weaker external networks receive this information. This process of information diffusion can be explained in light our interaction plots.

We observe that while the expected number of adaptive behaviors is initially higher among farmers with formal ties, this changes as the perceived peer effect to network partners' behaviors increases. Specifically, beyond a certain threshold of perceived peer exposure (say 5), the likelihood of adopting adaptive behaviors increases among farmers without formal ties. This means that as farmers increasingly interact with more adopters in their community over time, they become more receptive to different ideas and practices. This suggests the pivotal role of informal networks in facilitating the diffusion of adaptive behaviors as highlighted in previous study in India (Matuschke & Qaim, 2009). It is worth noting that while our model does not directly measure these temporal effects, we assume that these trends could emerge over time based on the observed relationship between formal and peer network interaction and predicted adaptive behavior. Future research with time-series data could provide more insight into the temporal dynamics of this process.

Besides network effects, our results indicate the importance of both psychological and economic factors in shaping farm households' decisions, particularly adaptation intensity. We found that farmers' inclination to make multiple adjustments is not solely a response to a single shock but rather a response to prior experiences with multiple shocks including drought, pest outbreaks, food price fluctuations, and floods, which is particularly relevant in highly vulnerable and climate-sensitive communities (Oppenheimer et al., 2014; Smit & Wandel, 2006). As expected, when farmers experience crop losses and perceive greater risk (Le Dang et al., 2014), they are more likely to adapt with greater intensity and use strategies aimed at protecting and supporting crop yields.

This observation is consistent with previous studies that have identified individual experiences with past damages as a key predictor of self-protective or adaptive actions in response to climatic hazards (Barnes et al., 2020b; Y. Huang et al., 2024; Jiao et al., 2020). Notably, we found a negative effect of wealth on adaptation intensity. This suggests that wealthier households may lean towards risk-averse strategies, possibly due to their existing investments in farming practices with high returns (W. Zhang, 2017). Conversely, it is also plausible that wealthier households, though have high risk tolerance, may adopt fewer adaptation behaviors, possibly relying on their financial resources to mitigate risks or engage in less climate-sensitive, off-farm activities as a means of buffering against climate impacts (Adnan et al., 2020).

We did not find any significant association between the size of owned farmland and farm households' decisions to adaptation intensity. However, the extent of farmland ownership emerges as a significant factor motivating farmers to adopt practices such as increased use of pesticide. This finding is consistent with prior studies in different contexts, for example, adoption of soil and water conservation techniques among maize farmers in Ghana (Abdallah et al., 2014) and the use of soil management practices such as chemical fertilizer among rice farmers in Northern Ghana (Donkoh & Awuni, 2011). This suggests households with larger owned farm size are more likely to investment in practices like pesticide use, getting benefit from maximum production with lower input costs per unit area (Y. Huang et al., 2024).

While our study provides valuable information, we acknowledge some limitations. First, we did not make any normative judgements on the usefulness or positive or negative or long-term sustainability of farmer adaptive behaviors. Second, influence-based network analysis demands longitudinal data for causal inferences, but we relied on retrospective data based on memory recall which could introduce bias. Third, our study primarily examined informal peer information networks and a limited number of formal networks. Further exploration of other informal networks, such as labor networks, could provide additional insights on adaptive decision-making processes.

While our study focuses on climate risk management, our finding on perceived peer effect may have broader applications beyond the issue of climate change. The influence mechanisms driving behavior change through peer interaction and exposure to perceived peer behaviors are likely relevant in other domains, such as health and education where behavior modification is desired. Future research could test this and explore how perceived peer-based interventions might be applied to promote health literacy and safety practices (Coman et al., 2020; Simoni et al., 2011).

3.6 Conclusion

Our findings identify the important role that perceptions of peer effect play in supporting farm households' learning and leveraging adaptive behaviors to manage climate risks, particularly in communities where formal support is limited or non-existent. Our findings highlight the interplay between formal and informal networks in influencing adaptation decisions, underscoring the need for future research to understand how different types of social networks interact and affect the diffusion of innovation and adaptive capacity in agricultural communities. This knowledge also provides guidance for policymakers and planners in designing adaptation programs that enhance the adaptive capacity of farm communities. Additionally, we recognize the psychological and economic factors as both barriers and entry points for interventions aimed at supporting farmers. Farmers' experiences with multiple shocks can heighten their perceptions of livelihood risks and motivate them to intensify their adaptive responses. Factors such as wealth, land ownership, and the age of households also play a role in adaptation decisions, offering insights for those aiming to strengthen climate resilience in agriculture and empower farmers to navigate the challenges of a changing climate to ensure the sustainability of resource-dependent farming communities in Cambodia and beyond.

CONCLUSION

This dissertation advances our understanding of the dynamics of challenges and local responses to resource and climate uncertainties in the context of dam construction. By identifying the processes and factors that hinder or motivate adaptation decisions among resource-dependent households, this work adds to the growing body of knowledge on adaptation in vulnerable regions. The mixed-method approach, which blends quantitative and qualitative methods, provides a comprehensive understanding of the multi-faceted nature of adaptation decisions process explored across three chapters. Moreover, the use of household and community-level case studies is crucial for capturing the localized impacts of climate change and resource management and diversity of responses to environmental stressors. The insights gained from the three chapters offer both theoretical advancements and practical applications for improving the adaptive capacity of vulnerable farming and fishing communities.

Chapter 1 provides a more nuanced understanding of dam impacts, particularly on natural, social, and financial livelihood resources in downstream farming communities. The findings reveal the varied impacts of dam construction on downstream communities, particularly on natural, social, physical and financial livelihood resources. Natural resource access decreases near dams, while physical resource access improves within 30 km after dam construction. Though there is financial resource access among downstream communities withing 30 Km, finding suggests some improvement among communities within 20 Km post-dam construction period. Communities' nearby irrigation dam experience increased social resource access post-dam, but overall, spatial and temporal variations highlight the complexity of dam impacts on local resources. These findings emphasize the need for better Environmental Impact Assessments (EIAs) and adaptation strategies to address the diverse effects of dams on downstream ecosystems and livelihoods.

Future research should include a larger variety of dams to develop a more comprehensive understanding of type-specific impacts. Additionally, exploring qualitative insights on measures, like migration patterns, social cohesion and their relationship to dam construction, could complement these quantitative findings.

Chapter 2 improves our understanding of drought risk perceptions among households within complex hydro-agricultural-fisheries systems, emphasizing the need for context-specific risk communication strategies. This chapter identifies key psychological and socio-economic factors—including households' drought knowledge, perceived adaptive capacity, organizational affiliations, and wealth status—as significant influences on risk perception. The proposed causal loop diagram (CLD) suggests a potential recurring and intensifying pattern of drought severity related to irrigation infrastructure, institutional and households' response to the environmental changes. These findings contribute to ongoing regional initiatives such as the 2021–2030 Basin Development Strategy and Mekong River Commission Strategic Plan 2021–2025, aiming to strengthen agricultural and fishing systems in the face of increasing drought severity.

Future research should focus on validating the CLD and applying system dynamics modeling to quantify behavioral patterns over time. This approach will help identify leverage points for policymakers to mitigate risks, offering further insights into the dynamics of drought response.

Finally, chapter 3 expands the limited knowledge on how perceived peer effects influence farmers' adaptive behaviors, particularly in regions with limited institutional support. By quantifying this process through social influence models, the chapter highlights the interplay between formal and informal networks in shaping adaptation decisions, which might affect the adaptation diffusion process in agricultural communities. Further, the chapter identifies the significant psychological and economic factors—such as farmers' experiences with multiple shocks, wealth, and land ownership—to leverage for interventions aimed at strengthening farmers capacity to manage climate risk in Cambodia and beyond.

Future research should explore how different types of social networks interact and influence the diffusion of innovations and adaptive capacity in agricultural communities, offering a deeper understanding of the social mechanisms that drive adaptation decisions.

Overall, this dissertation underscores the critical role of understanding the local challenges, their perception of the resource scarcity and climate uncertainties and role of different social ties in the adaptation processes, supporting local livelihoods while sustaining the agro-fisheries ecosystem in the Lower Mekong Region. It provides actionable insights for designing policies and programs that enhance adaptive capacity, particularly in resource-dependent communities, making it a vital contribution to the field of sustainable development and climate adaptation.

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APPENDIX A: MANN-WHITNEY U AND INDEPENDENT T-TEST RESULTS

Table 10: Preliminary test results showing temporal variation in proxy measures of diverse livelihood resources

Resource	Measures	Indicators	Unit of measurement	Results from non-parametric test	Independent t -test over time Null hypothesis: population means equal for both groups (2013 and 2019)				
					2013	2019	P-value	Direction	Estimated effect size (Cohen's d)
Natural	Access to land	Enagagement in cultivation	Proportion	Not significant	0.841 (0.233)	0.9 (0.01)	<0.001		0.329
		Ownership of land	Proportion	Significant	0.972 (0.049)	0.971 (0.053)	0.934	Same	0.013
		Parcel for livestock	Proportion	Significant	0.696 (0.260)	0.632 (0.171)	0.021	Decrease	0.290
		Parcel for aquaculture	Proportion	Significant	0.001(0.017)	0.788(0.306)	<.001	Increase	0.363
		Parcel for forest/wooded land	Proportion	Significant	0.129 (0.243)	0.048 (0.068)	<.001	Decrease	0.455
	Access to water	Engagment in fish catching	Proportion	Not significant	0.265 (0.306)	0.247 (0.298)	0.68		0.061
	Access to forest	Engagment in forestry	Proportion	Significant	0.002(0.014)	0.869(0.196)	<.001	Increase	0.623
Human	Access to laborers	Total household members available for e	Number	Significant	4.652 (0.654)	4.19(0.52)	<.001	Decrease	0.782
	Access to education	Education of HH head	Proportion	Significant	0.902 (0.169)	0.805 (0.110)	<.001	Decrease	0.683
	Access to knowledge and skills	Experiences in farming	Years	Significant	48.598 (4.961)	46.737 (3.374)	<.001	Decrease	0.439
		Access to agricultural information	Proportion	Not significant	0.357 (0.114)	0.361 (0.155)	0.855		0.030
Financial	Wealth	TLU	TLU	Significant	1.5(1.06)	5.664 (16.035)	0.072	Increase	0.366
	Access to credit	Access to credit/loan for agricultural pur	Proportion	Significant	0.175 (0.065)	0.474 (0.165)	<.001	Increase	1.387
	Access to banking facilities	Household using bank for credit	Proportion	Significant	0.147 (0.203)	0.329 (0.248)	<.001	Increase	0.804
	Access to microfinance		Proportion	Significant	0.488(0.292)	0.525 (0.245)	0.322	Increase	0.138
Physical	Access to irrigation facilities	Household with irrigation facilities	Proportion	Significant	0.243 (0.329)	0.32 (0.133)	0.002	Increase	0.306
	Access to market	Household using market either for sale o	Proportion	Significant	0.218 (0.051)	0.006 (0.022)	<.001	Decrease	0.534
	Access to school	Household with members attending scho	Proportion	Significant	1.132 (0.300)	0.195 (0.110)	<.001	Decrease	0.415
Social	Access to informal networks for credit	Relatives/friends	Proportion	Significant	0.253 (0.248)	0.01 (0.027)	<.001	Decrease	1.379
		money lender	Proportion	Significant	0.201 (0.226)	0.047 (0.083)	<.001	Decrease	0.906
	Access to network for agricultural information	Main source of agricultural information- f	Proportion	Not signficant	0.306 (0.310)	0.263 (0.174)	0.135		0.173
		Main source of agricultural information- (	Proportion	Significant	0.573 (0.334)	0.099 (0.102)	<.001	Decrease	1.922

APPENDIX B: MIXED EFFECT MODEL RESULTS

Table 11: Mixed effect model results (N= 483)

Variables	Natural		Social		Human		Financial		Physical	
	B	**EXP (B)**	**B**	**EXP (B)**	**B**	**EXP (B)**	**B**	**EXP (B)**	**B**	**EXP (B)**
Dam effect	-0.44*** (0.06)	0.64	0.08 (0.08)	1.08	0.11’ (0.05)	1.12	-0.38*** (0.06)	0.68	0.27*** (0.04)	1.31
Impact zone 1	-0.09** (0.03)	0.91	0.06 (0.04)	1.06	0.01 (0.04)	1.01	-0.03 (0.03)	0.97	0.05* (0.02)	1.05
Impact zone 2	-0.02 (0.02)	0.98	-0.08* (0.04)	0.92	0.01 (0.03)	1.01	-0.03 (0.02)	0.97	0.02 (0.02)	1.02
Dam type [IRR =1]	0.02 (0.02)	1.02	-0.13*** (0.03)	0.88	-0.01 (0.03)	0.99	0.02 (0.02)	1.02	0.03 (0.02)	1.03
Nightlight	0.03* (0.01)	1.03	0.02 (0.02)	1.02	0.01 (0.01)	1.01	0.01 (0.01)	1.01	0 (0.01)	1.00
Interaction [dam effect * Impact zone1]	0.05 (0.08)	1.05	-0.02	0.98	-0.13 (0.08)	0.88	0.3*** (0.08)	1.35	-0.04 (0.06)	0.96
Interaction [dam effect * impact zone 2]	0.13 (0.08)	1.14	0.13 (0.12)	1.14	-0.02 (0.08)	0.98	0.29*** (0.09)	1.34	0.01 (0.07)	1.01
Interaction [dam effect * dam type=IRRI]	-0.27*** (0.07)	0.76	0.24** (0.09)	1.27	0.06 (0.07)	1.06	0.02 (0.07)	1.02	-0.05 (0.05)	0.95
R^2	0.7		0.61		0.91		0.14		0.79	
Adj. R^2	0.69		0.6		0.9		0.13		0.79	

Note: value in parentheses is Standard Error (SE)
$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 12: Mixed effect model results (N= 100)

Variables	Natural	Social	Human	Financial	Physical
Dam effect	-0.50***	0.08	0.12*	-0.40**	0.27***
	(-0.07)	(-0.09)	(-0.06)	(-0.15)	(-0.05)
Impact zone 1	-0.13	0.09	-0.01	-0.04	0.03
	(-0.08)	(-0.09)	(-0.06)	(-0.15)	(-0.05)
Impact zone 2	-0.08	-0.07	0.08	-0.01	-0.05
	(-0.09)	(-0.1)	(-0.07)	(-0.16)	(-0.05)
Dam type [IRR =1]	-0.01	-0.17*	-0.01	0.01	0.06
	(-0.07)	(-0.07)	(-0.05)	(-0.13)	(-0.04)
Nighlight	0.02	0.01	0.01	0	0
	(-0.01)	(-0.01)	(-0.01)	(-0.02)	(-0.01)
Interaction [dam effect * Impact zone=1]	0.07	-0.05	-0.13	0.3	-0.03
	(-0.1)	(-0.13)	(-0.08)	(-0.22)	(-0.07)
Interaction [dam effect * Impact zone=2]	0.18'	0.12	-0.05	0.27	0.06
	(-0.11)	(-0.14)	(-0.09)	(-0.23)	(-0.08)
Interaction [dam effect * dam type=IRRI]	-0.23**	0.28**	0.06	0.03	-0.07
	(-0.08)	(-0.11)	(-0.07)	(-0.18)	(-0.06)
R^2	0.7	0.27	0.19	0.13	0.45
Adj. R^2	0.67	0.2	0.12	0.05	0.4

Note: Value is unstandardized Beta coefficient and value in parentheses is Standard Error (SE)
***$p < 0.001$; **$p < 0.01$; *$p < 0.05$

APPENDIX C: RESULTS FROM THEMATIC CODING

Table 13: Responses to the question "Why did you make those farm related changes" (Household survey, 2022)

Themes	Responses (%)
Increase rice yield/get better rice yield	15.6
Increase in insects/pest/weeds	50.6
Decrease in soil fertility/maintain soil fertility	48.1
Drought/no rain	16.9
Change in rice plantation method	45.5
Facilitate farming/save time	28.6
Changes in water availability	13
Irrigation canal nearby farm	2.6
No money	9.1

Table 14: Cross-tabulation between responses on "What changes have you made in your farming practices over past few years" and "Why did you make those farm related changes?"

Reasons	Respondents reporting increased use of these practices (%)				
	Irrigation	Pesticide	Fertilizer	Planting time	New farm equipment
Increase rice yield/get better rice yield	0.86	13.79	18.10	13.79	4.31
Increase in insects/pest/weeds	7.76	51.72	46.55	41.38	14.66
Decrease in soil fertility/maintain soil fertility	3.45	41.38	46.55	37.07	10.34
Drought/no rain	4.31	12.07	12.07	12.07	4.31
Change in rice plantation method	5.17	37.93	36.21	43.10	16.38
Facilitate farming/save time	5.17	23.28	19.83	25.86	14.66
Changes in water availability	5.17	2.59	5.17	10.34	2.59
Irrigation canal nearby farm	1.72	0.00	0.86	0.86	1.72
No money	0.00	1.72	6.90	6.03	0.86

Note:

1. Highlighted cells denote the significant association based on chi-square at p-value <0.05
2. Color denotes the strength of association based on Cramer value — Strong / Moderate

Note: Moderate strength refers to value between 0.3 to 05 and strong refers to value greater than 0.5 (Cohen, 1988)

APPENDIX D: RESULTS FROM PROBIT AND POISSON MODELS, AND MARGINAL EFFECTS TESTING

Table 15: Results from Poisson and Probit models (N=198)

Variables	Adaptation intensity (IRR) (Model a)	Adaptation choice (AME)		
		Irrigation use (Model b)	Pesticide use (Model c)	Fertilizer use (Model d)
Perceived peer exposure (PPE)	1.055*** (1.012)	0.019 (0.012)	0.052*** (0.014)	0.012 (0.016)
Ties-NGO	1.384* (1.146)	0.211** (0.068)	-0.205* (0.083)	-0.153' (0.085)
Ties-Government	1.579** (1.174)	0.084 (0.079)	0.091 (0.089)	0.033 (0.098)
Ties-Private	1.858*** (1.154)	0.119 (0.093)	0.118 (0.090)	0.199* (0.093)
PEE*Ties-NGO	0.947* (1.022)	0.062* (0.029)	-0.023 (0.033)	-0.045 (0.032)
PPE*Ties- Government	0.966 (1.023)	0.06 (0.047)	0.004 (0.034)	0.0002 (0.039)
PPE*Ties-Private	0.927*** (1.018)	-0.099 * (0.044)	-0.039 (0.029)	-0.014 (0.031)
Previous experience to multiple shocks	1.093' (1.049)	0.013 (0.026)	-0.016 (0.042)	-0.071 (0.044)
Crop productivity	0.844* (1.076)	-0.052 (0.043)	-0.099 (0.064)	-0.034 (0.069)
Land ownership	1.090 (1.058)	0.018 (0.016)	0.060' (0.032)	0.046 (0.034)
Wealth index	0.925* (1.033)	-0.027 (0.02)	-0.014 (0.028)	-0.033 (0.030)
Age	0.993* (1.003)	-0.001 (0.002)	-0.003 (0.003)	-0.003 (0.003)
AIC	744.996	136.129	248.125	279.205
log-likelihood	-359.498	-55.0647	-111.06	-126.603
Nagelkerke pseudo-R^2	0.219	0.344	0.271	0.105

*Notes: ***, **, * , ' showing significant at <1%, 1%, 5%, and 10% probability level, respectively; robust standard errors are in parentheses.*

Table 16: Results for how adaptation intensity is associated with informal and formal networks: tests of Average Marginal effects (AMEs) and second differences (N = 198)

Formal network	Informal peer network	First difference in AME		Second difference
		Without	With	
Ties- NGO	Perceived peer exposure	0.103**	-0.059	0.162'
Ties- Government	Perceived peer exposure	0.078*	-0.027	0.105
Private	Perceived peer exposure	0.100**	-0.157’	0.257**

*Note: ‘***’, ‘**’, ‘*’, ‘'’ refers to p-value <0.001, <0.01, <0.05 and <0.1 respectively*

Table 17: Results for farmers' adaptation decision (specific behavior) are associated with informal and formal network: tests of average marginal effects (AMEs) and second differences (N = 198)

Model	Formal network	Informal peer network	First difference in AME		Second difference
			Without	With	
Irrigation	Ties- NGO	Perceived peer exposure	0.004	0.062*	-0.057'
	Ties- Government	Perceived peer exposure	0.015	0.047	-0.045
	Private	Perceived peer exposure	0.038*	-0.099***	0.138***
Pesticide	Ties- NGO	Perceived peer exposure	0.078***	-0.023	0.101**
	Ties- Government	Perceived peer exposure	0.061***	0.0002	0.061
	Private	Perceived peer exposure	0.067***	-0.039	0.108***
Fertilizer	Ties- NGO	Perceived peer exposure	0.0295'	-0.045	0.074'
	Ties- Government	Perceived peer exposure	0.014	0.0002	0.014
	Private	Perceived peer exposure	0.017	-0.014	0.031

*Note: '***', '**', '*', ''' refers to p-value <0.001, <0.01, <0.05 and <0.1 respectively*