Adapting to a changing environment in the Mekong Delta: Analysis of socio-economic farm and commune characteristics

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Foreword

One condition I had set for my thesis topic: that it would be somehow related to human behaviour and decision making. I considered doing a field experiment on recycling behaviour with bioplastic. I considered looking into CO2 compensation in communities, a permit-based commercial aviation system with a tradeable cap for citizens, and I thought about doing research on a new way of government funding allocation (participatory value evaluation and a crowdfunding mechanism) in which citizens are directly asked for their preferences. Eventually I chose looking into adaptive behaviour of farmers in the Mekong Delta because it is strongly related to development and it has the potential of making an impact on people with relatively low living standards (as opposed to the other options).

Choosing this topic also brought a more personal benefit: going to Vietnam to do fieldwork. One month in the Mekong Delta, coordinating the field work at Can Tho University. Also, I have previously been to the Vietnam and the Mekong Delta before and have a great desire to return. Unfortunately, the coronavirus threw a spanner in the works. An early lockdown in Vietnam lead to some doubts on the possibility of doing fieldwork in Vietnam. Mid-March it became evident that going abroad was no longer an option.

This thesis has been written in collaboration with Maaike van Aalst, who is doing her PhD on adaptation pathways for socially inclusive development of urbanizing deltas. I would like to thank her and my supervisor, Eric Koomen, for their ideas, support, feedback and time they have spent discussing and reviewing my work on an almost weekly basis.

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1. **Introduction**

Vietnam is part of the top-ten most vulnerable countries to climate change and considered without capacity to sufficiently respond to potential future climatic disasters (Phuong et al., 2018). Especially the Mekong Delta, found in the southern part of Vietnam, is vulnerable. The Mekong Delta on average has a strikingly low elevation level of 0.8 meters above sea level (Minderhoud, 2019). Already 1.9 million ha out of 3.9 million ha in the Mekong Delta has been negatively affected by salinity intrusion. Estimations based on current carbon emission scenarios predict an increased sea level of 25 to 30 cm by 2050. This will cause saltwater to intrude up to 60 kilometres upriver on a regular basis and further in extensive periods of drought.

Another important factor that increases salinity levels in the delta is upstream hydropower dams. The Mekong River has been labelled the Battery of Southeast Asia (Schmitt et al., 2019). Full use of the hydropower potential of the Mekong River is estimated to lead to a reduction of sediment transport to the delta of over 90%. The delta needs the sediment for nutrients and to push back saltwater. The low elevation level of de delta combined with extended periods of drought and an uneven distribution sediment delivery causes serious environmental problems and threats to the livelihood of many Mekong Delta inhabitants.

Agriculture currently contributes to more than 21% of Vietnamese GDP. 80% of the population of the Mekong Delta is in some way involved in rice production (le Dang et al., 20 14). Vietnam finds itself among the top five exporting countries worldwide in agricultural products such as rice, rubber, pepper and coffee (World Bank, 2016).

As the current livelihood of many inhabitants of the Mekong Delta mainly depends on agriculture, change is necessary. Increased levels of salinity and water shortage will render current crop schemes infeasible. Households in the Mekong Delta will have to find new crop combinations or diversify their activities in other ways. In the last decade, strong environmental fluctuations were observed. Especially in late 2015 and early 2016 the Mekong Delta was hit hard by a period of severe drought and water shortage, resulting in increased levels of salinity in most of the delta and saltwater penetrating as far as 90 kilometres inland (Larson, 2016). This research investigates the resilience of households in the Mekong Delta to this climatic shock and tries to measure which household and commune characteristics matter most in responding to this shock.

This study aims to examine what determines the adaptive capacity of (agricultural) households in the Mekong Delta by answering the following research questions:

1. To what extent do socio-economic community and farm-level conditions determine the adaptive capacity of Mekong Delta farmers under changing environmental circumstances?
2. What key farm-level characteristics drive farmer adaptive capacity?
3. What key commune-level characteristics drive farmer adaptive capacity?

The first step to answering this question is clearly defining the two main components of the first research question; adaptive capacity and changing environmental circumstances. Adaptive capacity, in this thesis, is defined as the ability of a household to maintain their income level. The first paragraph of the chapter on literature discusses this more extensively. Changing environmental circumstances relate to changes in biophysical conditions. Annual fluctuations in temperature, precipitation, salinity intrusion, soil fertility and disease all potentially have a significant impact on the agricultural income of households in the Mekong Delta.

This thesis uses socioeconomic data at household and commune level and salinity data on district level to analyse. I use district salinity data to investigate which parts of the Mekong Delta witnessed changes in salinity that have a significant effect on the yield of certain crops.

From a bigger perspective, understanding the adaptive behaviour of farmers potentially contributes to global food security, livelihood security, biodiversity preservation and increased efficiency in policy design.

The remainder of this thesis is structured as follows. Chapter two consists of a literature review of previous research. Chapter three discusses methodology and data. The empirical analysis is found in chapter four. The thesis end with its conclusion in chapter five.

2. Literature

In this chapter I discuss the literature used for writing this thesis. I start by defining adaptation. In the paragraph on adaptation I discuss the different ways that adaptation can be defined, followed by an overview of how other papers captured adaptation in a dependent variable. In the second paragraph I discuss the perception and experience of changing environmental circumstances.

2.1 Defining adaptation

2.1.1 The concept of adaptation in agriculture

When Burnham (2016) looked into 35 empirical studies on the adaptation to changing climatic circumstances, he found a lack of conceptual clarity on the definition of adaptation. The international Panel on Climate Change (IPCC) has the following definition of adaptation (Burnham & Ma, 2016): *adjustment in natural and human systems in response to actual or expected climatic stimuli or their effects, which moderates harm or exploits beneficial opportunities.* Smit (2006) defines the human dimensions of adaptation to climate change as the process or actions in a given system (household, community, institution) that enable the system to adjust to, manage, or cope with changing natural conditions, hazards, risks, and opportunities.

A next step in defining the term adaptive behaviour starts at the distinction of different types of determinants of adaptation. The first type of determinants is objective (Phuong et al., 2018). This covers everything that is observable and not related to the perception of the individual. Think of age and years of education, network reliance and financial responses. The second type of determinants is subjective. Environmental perception, intentions and attitude are examples of this type.

I can also split adaptive behaviour into two other components (Burnham & Ma, 2017). The first one is adaptation intention. This is a measure of willingness to adapt to changing environmental conditions, not directly taking into account whether a person is capable of adapting. Adaptation intention is limited by the next component, adaptive capacity. This component mainly depends on objective factors such as resources and network reliance.

2.1.2 Operationalizing adaptation

Researchers that investigate farmer's adaptation to changing climatic circumstances often use similar approaches to their research. They start with focus group discussions that determine which different adaptive measures are being undertaken by the farmers that are being studied. The researchers then design a survey that includes these adaptive measures complemented with additional questions that are later used as explanatory variables.

The papers that were used to generate expectations of which socio-economic smallholder characteristics have an effect on adaptive behaviour used various dependent variables. Most of these articles used a binary dependent variable. The binary dependent variable took on various forms. Arunrat (2017) based his dependent variable on the dichotomous choice of adapting or non-adapting by asking farmers whether they had adapted or not. The author assumes that adapters perceive a risk reduction or expect an increase in farm benefits and non-adapters do not adapt as a result of barriers. Tien Dung (2018) based his dependent variable on whether a Vietnamese rice farmer decided to adopt a specific rice seed technology, as did Mariono (2012) among Philippine rice farmers. Kibue (2012) asked their respondents whether they had taken certain adaptive measures. If a respondent had taken one of these measures the respondent was labelled as an adapter. Otherwise the respondent was labelled as a non-adapter.

Other research used a continuous variable to capture adaptation. Phuong (2018) used the number of adaptation measures undertaken by an individual as a continuous integer dependent variable. Nielsen (2013) used risk aversion as a continuous dependent variable. The higher the risk aversion of a farmer is, the higher that individuals' risk aversion. Risk aversion is used as an explanatory variable by Mariano (2012), for which he uses crop diversification as a proxy. The author argues that having more than one crop decreases risk of a crop failure, which means someone is risk averse. He then expects that higher risk aversion will lead to the adoption of new technologies because of increased expected household utility.

The emphasis of this thesis was initially on objective determinants and adaptive capacity as this offers more room for quantification and therefore quantitative analysis. However, throughout most of the consulted papers, a lack of research on and an accentuation of the importance of cognitive/psychological and hard-to-quantify determinants intensivied interest in this part of adaptive behaviour of farmers. Constructing a survey that investigated both objective and subjective determinants of the adaptive intention and capacity of farmers would allow investigating adaptation from multiple angles,

As the research plan changed as a result of the 2020 pandemic, the emphasis of the thesis moved once again towards the objective determinants of adaptive capacity. Being limited to analysing existing datasets for the most part ruled out the opportunity of investigating the dynamics of the subjective determinants of and intention towards adaptation. For this reason, I needed to distil a definition of adaptive capacity from the available data. After initial analysis of the data it became evident that income shares from sources other than agriculture got bigger each year and the relative importance of agriculture seemed to decline. As a result of this preliminary conclusion I decided that only looking at fluctuations in agricultural income because of environmental variability would not be sufficient to investigate the adaptive capacity of farmers.

Phimister et al. (2005) used the variance in farm and off-farm income calculated of each farm over six years with one observation for each year. They ran OLS regressions with average variance or the deviation from the average variance as the dependent variable. They found that a diversified portfolio of activities does not lead to a lower income variability. Key et al. (2017) use a wide variety of measures of farm income variability based on the substantial amount of research done on income variability of non-farm households. They mainly focussed on absolute and percentage change in income between two years and (variations of) the standard deviation and variance of income. They also measure volatility by the absolute value of the actual change in income divided by the average of income of two years. Key et al (2017) focussed on a period of 17 years.

Dunn et al. (2000) use a panel of 282 households over a time period of 24 years to determine which factors influence farm income variability. They use both cross-sectional and panel data to analyse farm income with four different definitions of their dependent variable. Firstly, they use the standard deviation of farm income. Second and thirdly, they use (the average of) the absolute value of negative deviations from the mean accrual net farm income. Lastly, they use the annual change of farm income.

Berhe et al (2017) use household income of agricultural households as a dependent variable in panel analysis over a period of five years with observations each year. The authors attempt to determine the effects of different adaptive measures and household income in previous years on the income of households with agricultural income. The authors designed their own questionnaire which enabled them to include perception of climate change and various adaptive measures effectively.

The four papers above all had a panel that spanned a longer period of time that enabled them to look at deviations from the average income over their period of interest. As this thesis only has three observations per household in a span of five years this becomes difficult. For this reason, income change between two periods will be used to model adaptation. This will be done in relative and actual change. Actual change as suggested by Dunn et al. (2000), but not in absolute terms. Absolute terms meaning not keeping the sign in mind. Relative change as suggested by Key et al. (2017), also not in absolute terms. As both these authors intended to investigate income volatility, they used absolute change in income. This thesis makes a distinction between income decrease and increase. Because most literature on adaptation used a binary dependent variable, adaptation will also be modelled as a choice variable in this thesis. More on defining adaptation in the methodology chapter.

2.2 Perception and experience of environmental circumstances

Most empirical research shows that many farmers are aware of changing environmental and climatic conditions. Some of the literature quantifies perception of changing environmental conditions (Arunrat et al., 2017; Kibue et al., 2016; Phuong et al., 2018), which is often 75% or higher among interviewed or surveyed smallholders. However, this high level of awareness among smallholders does not directly indicate high levels of adaptation.

Although perception is found to be pivotal in the understanding of adaptive behaviour of farmers (le Dang et al., 2014), Kibue (2016) found that less than half of the farmers she researched actually took adaptive measures. The most important reasons given for not adapting in spite of perceived changing conditions were lack of climate and adaptive technology information, attachment to tradition, lack of credit access and social barriers. Phuong (2018) found that of the farmers that perceived a change in temperature and precipitation, only half of them perceived a serious impact from these changing circumstances on their agricultural practices. The other half perceived almost no impact. 94% of the interviewed farmers expected that climate change induced droughts will threaten their current farming methods in the future.

Perceiving changing environmental conditions can also have a negative effect on adaptive behaviour. Schad (2012) finds that farmers in North Vietnam perceive increased flooding as a result of a mix of external factors of which climate change and water management failures are the most prominent. Many of the farmers do not link the increased flood risk to their own land usage practices and do not feel any responsibility or need for individual adaptation.

According to Le Dang (2014), experience is very important for the perception of changing environmental conditions. He found that during focus groups, the participants mainly talked about what they had experienced rather than what they had heard of or saw somewhere else. Geographical characteristics have a large influence on the willingness to perceive changing environmental conditions. Farmers further upriver do not pay much attention to sea level rise and salinity intrusion, while this is crucial to keep a close eye on for farmers close to the ocean. This strengthens the argument that experience is important for the perception of changing climatic conditions.

Furthermore, Le Dang (2014) argues that the expectation of farmers with respect to climate change causes perception of climate change to be irrelevant because the perception is too much biased by expectation. Lastly, Le Dang (2014) finds that only a small number of farmers perceive the potential benefits of changing environmental conditions such as increased soil fertility and crop diversification possibilities.

On the other hand, Burnham (2017) finds that perceived risk of changing climatic circumstances lowers the adaptation probability of a farmer. One possible explanation for this relationship between higher perceived climate-related risks and lower adaptation intent is that smallholders may view the risk of adapting as greater than the risk of not adapting because they are concerned about other non-climatic risks. They found that perceived self-efficacy had the largest impact on adaptive behaviour.

2.3 Household characteristics

2.3.1. Socioeconomic

Already in the theoretical analysis of all consulted literature, numerous differences were found in which characteristics drive or hinder adaptive behaviour. Most of the literature shows some consensus, as multiple papers find that age, education and income have a significant influence on adaptive behaviour (Arunrat et al., 2017; Kibue et al., 2016; Phuong et al., 2018; Tien Dung et al., 2018). However, while most authors found that being male has a positive effect, Kibue (2016) found that being female has a positive impact. Variables such as farm size, credit access and owning land were primarily mentioned as having a positive effect on adaptive behaviour. Having a small farm was found to have a positive effect by Burnham (2015) on adaptive capacity as it requires less effort and investment to change what the land is being used for.

Nielsen (2016) made a comparison in her literature review of a little less than 10 papers where she found that no consensus at all exists on variables such as gender, age, income and education. Furthermore, she mentions that social capital is often neglected in the analysis of farmer adaptive behaviour and risk preferences.

The variables most often found to have a positive effect on adaptive behaviour are farm income, education, farm size and tenure. Other characteristics often found are credit access, extension and knowledge sources. Farm income and education are in line with the expectations formed in the previous paragraph. The fact that the collective results find little opposition strengthens the findings. Farm income and credit access are found to be insignificant (Tien Dung et al., 2018). However, he does not get into this. A possible explanation for this deviation is that the research done by Tien Dung (2018) is based on the lowest number of respondents (n=420).

Age is the variable on which the consulted literature is most conflicted. Mariano (2012) found that, on average, non-adapters are older than adapters. One possible explanation for this is given by Phuong (2018), who states that high education and young age is often linked to migration as more prosperous opportunities are available for them elsewhere. Furthermore, Mariano (2012) found age to have an insignificant effect on adaptive behaviour. This is backed up by the findings of Tien Dung (2018). Arunrat (2017) found higher average age in the group of adapters.

2.3.2 Diversification

Babatunde et al. (2009) use three measures of diversification to determine how diversification affects household income. Firstly, they count the number of income sources for each household. Secondly, they use the share of off-farm income in total income. Lastly, they use the Herfindahl diversification index. The Herfindahl index originates in the industrial literature. Here it is used as a measure of concentration in a certain industry but can also be used for households. The index uses the sum of squares of each income source (Ersado, 2005). This leads to a value of one if a household has fully specialized its income to one source. As the opposite of specialization is diversification, subtracting the value of the Herfindahl index from one leads to the Herfindahl diversification index.

2.4 Commune characteristics

Much empirical research observes that extension related variables are among the strongest determinants of adaptive behaviour and first mentioned by farmers in interviews when asked what they need. Agricultural extension is the delivery of (scientific) knowledge to farmers to improve their productivity, food security and livelihood. The strongest determinant means a one unit increase in the explanatory variable increases the likelihood of farmer adaptation more than any other variable. Extension related variables in table 1 are demonstration attendance, training attendance and extension access.

Mariano (2012) finds that demonstration attendance, training attendance and access to extension workers have stronger marginal effects than any other variable. Extension workers are often government officials or NGO workers that teach farmers about new crops, new technologies and other things that might benefit farmers. Kibue (2016) detects that extension is the objective variable with the strongest effect on adaptation, after the subjective determinant perception of climate variability perception and knowledge of climate impacts. Tien Dung (2018) notes that extension has the strongest effects on adaptive behaviour of all variables that were included in the regression. Arunrat (2017) finds that training attendance (as a substitute for extension) together with credit access have the strongest impact on adaptive behaviour.

Burnham (2017) discovers that almost no farmers (6%) think they can adapt to changing climatic conditions without information or assistance from the agricultural professionals or the government. Most farmers (81%) believe they can adapt relatively easy with information or assistance. He also asked farmers whether they were likely to adapt their practices based on current knowledge and situation, of who only 3% said it would be very likely. They then asked whether they were likely to participate in a university or government program that would help them make changes. 97% indicated that they were somewhat or very likely to attend. When asked what farmers could do to increase their learning capacity, the main suggestions were more training courses and learning programmes for supporting adaptation (Phuong et al., 2018).

However, Burnham (2017) also found that smallholders in a certain area perceived their own ability to adaptive to changing environmental conditions as very low because of dependency on state involvement. In a period of one year, the Chinese government set up a canal system, developed cash crop opportunities and organised multiple workshops a year. The farmers in these areas used to live in a different area that needed to be cleared for infrastructure development and used to be livestock farmers. These findings indicate that sudden significant and assisted changes to farming practices have a negative effect on self-efficacy.

Extension related variables seem to have a significant effect as they are mentioned in many of the consulted literature. Multiple papers found their effects to be the strongest among all variables that were included in their empirical work. Extension helps farmers increase their perceptive capacity, self-efficacy (when extension is presented in moderation), enables their learning capacity and is clearly asked for by them. Furthermore, in communal context, extension offers additional benefits, which will be discussed in the chapter on community characteristics.

Nielsen (2013) did some interesting work on community characteristics by asking farmers about their network reliance and their altruistic norms. For network reliance, she asked farmers if it would be easy to borrow money for education, health, a social event, a buffalo or labour assistance from first-degree relatives/extended family/friends or the village head. They asked this question for each social relation separately. The questions on norms assess whether an individual thinks that when another villager takes a risk and loses (invest in new technology, which does not positively affect output or profit), other villagers should help that person.

The two variables may offer interesting insights into communal independency. Imagine an area where institutional tools such as credit and insurance are not available. Strong network reliance and helping norms in a community would likely lead to a more adaptation than a community with weaker reliance and norms.

Both the helping norm and network dependence reduced risk aversion and positively affects adaptive behaviour, except for network dependence on first-degree family members. However, network dependence on friends and the village head were insignificant, which, according to Nielsen, highlights the value of family in Vietnamese society.

Both Le Dang (2014) and Kibue (2016) found that socio-cultural relationships and norms have a negative effect on adaptive behaviour in rural Vietnam and China. In the paper of Le Dang (2014), farms that have been in the family for generations increase the likelihood of farmers to not adapt because new crops go against valued family tradition. In the paper of Kibue (2016), farmers are hesitant to adopt new technologies because they fear the communal consequences of departing from local traditions.

Mariano (2012) found that being a farmer close to a market leads to lower levels of adoption of new technologies. The findings of Tien Dung (2018) and Burnham (2016) oppose this. A common characteristic of market distance is that it has a negative effect on adaptive behaviour (Arunrat et al., 2017). One might reason that market proximity leads to less transaction costs are needed to sell wares on the market, making it more attractive to be a commercial farmer. However, Mariano (2012) describes market proximity as a gateway to distraction from farming such as non-agricultural employment. As this thesis focusses on the capacity of a household to maintain a certain level of income, the argument of Mariano does not apply. As both lower transaction costs and non-agricultural employment opportunities are likely to increase household capacity to maintain a certain level of income, market proximity is expected to have a positive effect. I initially intended to include non-farm opportunity as an explanatory variable. Unfortunately, the available data did not permit this.

According to Burnham (2017), social identity and an individuals' perception of his place in a community can have both a negative and a positive effect on adaptive behaviour. A individuals' perception of the social dynamic of a community and his/her place in it determines whether that individual feels comfortable asking for help or interprets information given to him by community members. Smallholders comply to opinions of influential people, using adaptation strategies that are deemed appropriate for a certain social standing (Singh et al., 2016). This affects adaptive behaviour but is hard to quantify.

2.5 Changing environmental circumstances

The Mekong Delta is often divided into three ecological zones (Can, 2016). Coastal areas near the South China Sea and the Gulf of Thailand often have a soil salinity level somewhere between 18‰ and 30‰ and cover 36% of the Mekong Delta. Brackish water zones are found a little further inland and usually have a soil salinity level between 0.4‰ and 18‰ and covers 27% of the Mekong Delta. Further inland are the freshwater zones with a soil salinity level under 0.4‰ and covers 37% of the Mekong Delta.

The feasibility of a crop in an area with a given level of soil salinity strongly depends on the salt tolerance of that crop. According to Smajgl et al. (2015), replacing sensitive rice varieties with salinity-tolerant varieties could be an effective measure in rice farmer adaptation. He found that tolerant species only marginally decrease their yield at 3 grams per litre of water while sensitive varieties losing more than half their yield at this level of soil salinity.

According to the Food and Agricultural Organization of the United Nations (2017), each crop has a linear yield function that is decreasing in salinity levels. Each crop has a salinity threshold value up until which the crop does not lose any yield. The FAO-Threshold value for rice is reached at 1.92 grams of chloride per litre of water. After this threshold is reached, each additional gram of chloride per litre of water causes a yield decrease of 18.75%. Here, no distinction is made between rice species with different levels of tolerance.

As the utilized datasets do not make a distinction between different rice varieties this thesis will use the FAO-threshold to investigate effects of salinity on rice yields. Other crops in the delta are grouped together in the data and are beyond the scope of this thesis.

Mariano (2012) found that farmers in drought and flood-prone areas are less likely to adopt new technologies. This may seem counterintuitive at first. In the chapter on perception and experience I discussed that being in a certain area with a high risk of salinity intrusion, farmers are more likely to experience changing conditions and perceive the importance of adapting. Mariano argues that fear of crop failure and risk aversion in drought and flood-prone areas keeps farmers from investing. Also, in the chapter on perception and experience, Burnham (2017) finds that smallholders that perceive a higher amount of livelihood risk reported a lower likelihood of making changes to their agricultural practices. Furthermore, adapting to floods and droughts require high costs as they require certain infrastructures such as dikes and irrigation systems. Multiple studies (le Dang et al., 2014; Mariano et al., 2012; Phuong et al., 2018) have found these types of investment to be perceived by farmers as government responsibility, partly because farmers lack the financial means for these investments.

2.6 Hypotheses

I have formulated seven hypotheses based on the reviewed literature of this chapter. The first four hypotheses are concerned with socioeconomic household characteristics. The fifth and sixth hypothesis are focussed on socioeconomic commune characteristics. The last hypothesis embodies the environmental element of this thesis.

1. Farmers that have a high income have a higher adaptive capacity to environmental change
2. Farmers that have a large farm have a higher adaptive capacity to environmental change
3. Farmers that are better educated have a higher adaptive capacity to environmental change
4. Farmers that have diversified their income sources have a higher adaptive capacity to environmental change
5. Farmers that are part of a community with an extension centre have a higher adaptive capacity to environmental change
6. Farmers that are part of a community that is close to a commercial centre/market have a higher adaptive capacity to environmental change

7. Farmers that are less exposed to environmental pressure have a higher adaptive capacity to environmental change

For each hypothesis one or more variables are included in the empirical analysis that allow the hypotheses to be tested. In the next chapter these variables will be explained.

3. <u>Methodology</u>

This thesis attempts to understand what socioeconomic factors drive the adaptive capacity of farmers in the Mekong Delta by analysing household and commune data in cross sectional and panel form. First, a body of theoretical and empirical literature was reviewed to determine how others examined the adaptive capacity of farmers in Vietnam and other countries. The literature review was also conducted to find which socioeconomic factors were found to have effects on the adaptive capacity of farmers. The literature review formed the base for translating the research questions into testable hypotheses. After researching various studies and approaches to analysing the adaptation of farmers to changing environmental circumstances I will perform OLS and logit regressions on income and the three definitions of income change that will be elucidated in section 3.2.1. This is followed up by panel fixed effects and random effects models as suggested by Berhe et al. (2017)

This chapter continues with an overview of the different datasets that were used for the empirical analysis. Secondly, I discuss how the dependent and explanatory variables are specified. Lastly, the limitations of the thesis are briefly discussed.

3.1 Datasets

For the quantitative analysis of adaptation in the Mekong Delta three datasets were used. The Vietnam Household Living Standard Survey (VHLSS) formed the base of the analysis. The VHLSS is a biannual survey undertaken among Vietnamese households. I use the 2014, 2016 and 2018 data to investigate changes in household income as a function of characteristics of that household and the commune that it is located in. All relevant household characteristics are found in the VHLSS. Using observations for 2014, 2016 and 2018 provides us with a chance to investigate the capacity of households to cope with an environmental shock. In late 2015 and early 2016, a long period of drought occurred with increased levels of salinity intrusion. The VHLSS household data enables us to answer the first three hypotheses as it contains data on income, education and farm size. Approximately 40 percent of the households that are surveyed in any given year were also surveyed two years prior. This overlap was used to create a balanced panel of 1735 households that were surveyed in 2014, 2016 and 2018.

I attempted to obtain all commune characteristics through the VHLSS counterpart that is concerned with communes. Unfortunately, this dataset provides data only on a part of the communes that were needed. The VHLSS commune data would have been very useful as it is conducted in the same years as the VHLSS household data.
In the light of the unavailability of the VHLSS commune data, I have decided to use the Vietnamese Agro census. This dataset is collected once every five years and covers a much larger population than the VHLSS does. Both VHLSS surveys and the Vietnamese Agro census are organized and undertaken by the Vietnamese government.

The last dataset contains measurements of soil salinity in most districts in the Mekong Delta from 2010 to 2017. This dataset helps us with adding an environmental element to the model. The effect of salinity only captures a part of how this environmental shock affected people living in the Mekong Delta. The salinity data offers a chance to investigate the effect of increased salinity levels on the crop yields.

3.2 Variable specification

3.2.1 Dependent variable

While exploring the available data it became obvious that agricultural income and revenue shares decreased as income shares from renting out land and waged labour increased. This was an indication that only looking at agricultural income omits one of the important adaptive measures for many agricultural households: finding additional income outside of agriculture.

As the main purpose of this research is investigating the relation between different socioeconomic farm- and commune characteristics and the capacity of households to cope with changing environmental circumstances, I will use changes in household income as a proxy for adaptation. A household that is able to maintain a certain level if income despite increased environmental pressure is considered a household with a certain degree of adaptive capacity.

Three definitions are proposed to work total income into a workable dependent variable:

1. Actual changes in income. The actual change in income is measured simply by taking the difference in household income between either 2014-2016 or 2014-2018.
2. Relative change in income. Relative changes are defined as the difference between income in year s and year t, divided by income year t. Relative change in income, as argued by Key et al. (2017), takes into account that the income level in the base year as an income changes of $ 5.000 can have very different consequences for a household with a yearly income of $ 10.000 than for a household with a yearly income of $ 100.000.
3. Binary: Income decrease versus stable or increased income.

3.2.2 Explanatory/independent variables

Socioeconomic household characteristics

Farm size is calculated based on the agricultural land used by a farmer. This includes plots for annual and perennial crops and plots for aquaculture. This variable is used in hectares during analysis. This variable is included to test the second hypothesis

Education is determined by the years of education of the household head. The maximum value this variable can take is twelve and represents a university degree, the lowest value after zero, one, represents primary education. This variable helps test the third hypothesis.

Household size is determined by the total number of family members living in the household. Age and gender are determined by the age and gender of the household head.

Diversification, with which the fourth hypothesis is concerned, is measured by three variables. Firstly, it is measured by the diversification index as described in the literature review by Ersado (2005) and Babatunde (2009). A fully diversified household with an index value of one has income from all eight income categories. The farm income categories are crop production, aquaculture, husbandry, forestry and agricultural services. The other three categories are wage, business income and income from renting out land.

The second variable that helps in testing the fourth hypothesis is the agricultural income share. For each household the percentage of total income that is obtained in agriculture is used as an explanatory variable. This is similar to what Babatunde (2009) did with using off-farm income share as a regressor in his analysis. Thirdly I use a dummy variable which takes the value of one if one or more household members receive wage for non-agricultural labour, and zero otherwise. As will be visible in the descriptive statistics, agricultural income shares decrease while the income share of waged labour increases each year. It will be interesting to see if type of diversification not only gains a bigger income share for households, but also benefits the adaptive capacity of households.

Four dummy variables are included in the analysis for the base year income quartiles. The quartiles are formed by splitting household data into quartiles using Stata. These are included to test the first hypothesis. Each household is placed in one of the four income quartiles based on its income. The first income quartile will be used as the base category in each regression where the income quartiles are included.

The last socioeconomic household characteristic modelled in this thesis is perception. To include it, a dummy variable is formed that takes the value of one if a household believes their living standard has stayed at the same level or increased. It takes the value of zero if the household living standard has decreased. This variable is included to measure if the household's perception of their change in living standard affects the adaptive capacity of a household.

Socioeconomic commune characteristics

For each commune, the number of households according to the national poverty line is divided by the number of total commune households to get a share of poor households per commune. This variable is included to see if living in a community with a certain share of poor households affects the adaptive capacity of households.

Three dummies are included that are related to infrastructure. A dummy for whether a commune is reachable by paved road, one for whether the entire commune has access to the national electricity grid and a final dummy for whether the commune is connected to a centralized water supply.

Two dummies are included related to other commune facilities. The first dummy is concerned with the availability of extension officers in the commune. The second one with the availability of training courses mainly related to agriculture. These dummies are included to test the fifth hypothesis.

The distance of the commune headquarter to the nearest market is included to see if distance to the nearest market affects the adaptive capacity of households. This variable is included to test the sixth hypothesis.

Changing environmental circumstances – soil salinity

To test the last hypothesis, soil salinity is operationalized by a measure of exposure for each household. The percentage change in salinity is used as an explanatory variable. The variable only measures exposure if two conditions are met. Firstly, a household lives in a district where salinity measures have been higher than one gram per litre of water in 2014, 2016 or 2018. If soil salinity levels have been lower than that in the period that is researched, no significant changes in crop yields should follow as a result of salinity. Secondly, a household has agricultural revenue. Households that rely on other income sources are not likely to be directly affected by increased salinity levels.

3.4 Data limitations

Using various data sources limits the usability of the data. Most of the data used are a result of surveys conducted by government officials of Vietnam. Surveys are prone to several biases. Respondents may answer questions (subconsciously) untruthful in a desire to conform to social norms, as a result of wishful thinking or simply because they do not remember the past correctly.

Every dataset used does not cover all communes in the Mekong Delta. Each dataset has some missing communes. Different communes are missing in each dataset. As a result, the number of households I am able to investigate is limited by the use of various datasets. Furthermore, the VHLSS data seems to be suffering from selection bias to a certain degree. When merging the VHLSS household data with the Agro census data, any commune that has a share of poor households over 41% in the Agro Census is not found in the VHLSS household data. Additionally, every commune found in the Agro Census that is not connected to the national grid is not represented in the VHLSS household data. This leads to a bias in the data as these communes and the households that live in them are not included in the analysis.

4. Empirical results

4.1 Descriptive statistics

In this paragraph I describe the datasets that were used. The paragraph mainly explains income composition and diversification of households and how they develop from 2014 to 2018.

4.1.1 Households

All descriptive statistics and tables in this section are created using the VHLSS data.

Income and income changes

In this section I discuss how revenue from different sources evolve in relative importance from 2014 to 2018. I first do this for all households in our Mekong Delta panel and then limit the analysis to only households with agricultural revenue.

Table 1. Average gross revenue shares per income category

Variable	2014	2016	2018
Wage	.510	.525	.544
Land rent	.136	.137	.14
Business	.550	.561	.564
Agriculture	.510	.502	.471
Other	.160	.165	.193

Note: The share for a certain income source for a given year gives the average share that income source for all households that have any income from that income source. All households that do not have income from that source are not included in the calculation of averages.

The table above displays the average gross revenue shares for five income categories. Other income includes income from gifts, social benefits, interest and donations. The table shows that while business and land rent revenue shares seem to be stable, wage and other revenue go up as much as agricultural revenue goes down.

Table 2. Average gross revenue shares for households with agricultural revenue

Variable	2014	2016	2018
Wage	.416	.432	.444
Land rent	.123	.131	.130
Business	.409	.423	.440
Agriculture	.510	.502	.471
Other	.135	.134	.164

In the table above I see that for households with agricultural revenue, all revenue sources increase in relative importance over time except agricultural revenue. Over the years, the share of agricultural households that only have agricultural revenue is stable at approximately 24 percent.

Income - Net Income

I can do the same analysis as above based on agricultural and business income/profit instead of gross revenue.
The negative values, even for wages, are the result of the negative profit (loss) values of agriculture, which translates into negative values for the shares of other income sources. Negative values only occur in agricultural income.

Table 3. Average income shares

Variable	2014	2016	2018
Wage	.498	.517	.523
Land rent	.15	.156	.156
Business	.398	.393	.421
Agriculture	.434	.403	.400
Other	.168	.180	.200

Note: For business and agriculture, some negative values have been set to zero. This was less than 1% of households

A trend is visible from 2014 to 2016 and 2016 to 2018: all average income shares rise except for agriculture, which declines. The average share of wage has been biggest throughout the years when considering net income. It already was in 2014 and the relative importance continues to grow.

Increasing and decreasing household revenue

Most household incomes are not exactly the same in two given years. To assess changes in income, I will apply a similar threshold value as used for defining monoculture. If household income in 2016 is at least 10% higher than it was in 2014, the household income has increased.
If household income in 2016 is 90% or less of that household's income in 2014, the household income has decreased. The same can be done for income changes from 2016 to 2018.

Vietnam witnessed an inflation of 4.7 percent from 2014 to 2016 and an inflation of 6.3 percent from 2016 to 2018. Together these percentages sum up to an inflation of 11.3 percent from 2014 to 2018. In assessing whether a household has been able to maintain a certain income level it is more informative to look at real income changes. In the rest of this thesis, every analysis related to income has been corrected for inflation.

Table 4. Household revenue changes

		100%	90%
2014-2016	Increase	982	840
	decrease	729	592
	No change	24	303
2016-2018	Increase	1145	1018
	decrease	565	463
	No change	25	254

Clearly more of the households in the panel had an increase in household revenue between 2016 and 2018 than between 2014 and 2016. This is in line with our expectations of the negative effects of the environmental shock in late 2015 and early 2016. The 24 households that had no change in income between 2016 and 2018 all had no income in 2016 and 2018. An explanation for this might be that only income generated by the household itself is included.

Agricultural revenue

In 2014, 1211 of the 1735 households had agricultural revenue. In 2016 more farmers started farming than stopped, resulting in an increase in households with agricultural revenue to 1233. Between 2016 and 2018 more households stopped than started farming, resulting in 1192 households with agricultural revenue. This development fits well with the narrative of an environmental shock: more people picking up agriculture as a(n) (additional) mean of living before the shock, and more people giving up on agriculture after the shock. It will be interesting to see what characterizes the households that have started and stopped farming between 2014 and 2018. Between 2014 and 2016, 94 households stopped farming and 116 households started farming. Between 2016 and 2018, 135 households stopped farming and 94 households started farming.

Table 5. Household agricultural revenue changes

		100%	90%
2014-2016	Increase	641	569
	decrease	686	592
	No change	0	166
2016-2018	Increase	747	673
	decrease	578	511
	No change	2	143

Income, agricultural income and non-agricultural income

Table 6. Household income changes

		100%	90%
2014-2016	Increase	1006	861
	decrease	706	579
	No change	23	295
2016-2018	Increase	1166	1061
	decrease	545	441
	No change	24	233

The *No change* outcomes for the 100% row all represent households that had no income. No household that had an income had the exact same income level after two years.

In 2014, 327 of the 1735 households had no income from other sources than agriculture. Of those 327 households, 35 had no income at all (benefits, donations etc. are not included, they are likely to have some form of income that is not a direct result of their labour or capital input).

In 2016, 318 households had no non-agricultural income with 42 households having no income.

In 2018, 345 households had no agricultural income with 51 households having no income.

Table 7. Household agricultural income changes

		100%	90%
2014-2016	Increase	649	582
	decrease	678	621
	No change	0	124
2016-2018	Increase	760	704
	decrease	567	494
	No change	0	129

From the table above and the table below, it is clearly visible that the shock in in 2016 hit much harder in agricultural income that in other income sources. More than half of the households with agricultural income saw a decrease in their agricultural income. 65% of the households with non-agricultural income saw their non-agricultural income increase.

I am not sure why the number of households without any income increases both from 2014 to 2016 and 2016 to 2018. This might be because of increased migration and remittances. But even then, 3% of the households in 2018 having no income seems strange. When considering revenue instead of income, the number of incomeless households remains the same.

Table 8. Household non-agricultural income changes

		100%	90%
2014-2016	Increase	938	825
	decrease	585	489
	No change	0	209
2016-2018	Increase	1015	935
	decrease	517	456
	No change	0	141

Income changes and perception

Opportunities for investigating the household perception of their ability to adapt to changing environmental circumstances were limited. The VHLSS household survey offers one. The survey asks households whether they believe their household's life has improved compared to

5 years ago. This ruled out using 2014 and 2016 data as five years ago relates to respectively 2010 and 2012 (approximately, at the moment the survey is taken). For both years no data is used in this thesis. In 2018, however, respondents are asked whether they believe their household's live has improved compared to 2014.

While 598 of the 1735 of the panel households had a lower income in 2018 compared to 2014 (adjusted for inflation), Only 111 panel households reported a worsened household's life. Strikingly, less than half of the households that reported a worsened household's life had an income in 2018 that was lower than the household's income in 2014.

The survey also asks households what the main reasons are for the lack of household's life improvement. Environmental stressors such as floods, droughts, cattle epidemic and decreases in arable land are among the least mentioned both in 2016 and 2018.

4.1.2 Environmental circumstances

As mentioned before, changing environmental circumstances are investigated in two ways in this thesis. I use the drought in late 2015 and early 2016 and argue that households that depend mainly on agriculture for their livelihood had a lower capacity to adapt to this drought than households that have a more balanced income portfolio. Secondly, I investigate changes in soil salinity levels and look at districts that witnessed a significant change in salinity levels. I determine yields per hectare for total agricultural revenue combined with total farm size and for rice yield per hectare. Other crops are grouped together and do not lend themselves well for this type of analysis.

Salinity

I have compared average yearly salinity levels for each Mekong Delta district that is available in the data (126 out of 134 districts). From 2014 to 2016, salinity levels increased in almost every district. 2014 to 2016 only saw a decrease of salinity levels in 8 districts. Between 2016 and 2018, a 116 of the 126 districts witnessed a decrease in salinity levels. Between 2016 and 2018 there were still 9 districts that had increased salinity levels.

Interestingly, most districts that saw increasing salinity levels between 2016 and 2018 had decreasing salinity levels from 2014 to 2016. All districts that had an increasing salinity level from 2014 to 2016 had a decreasing salinity level from 2016 to 2018.

The districts that were spared in 2016 and hit in 2018 are all on the western part of the south coast of the Mekong Delta and two island districts that are part of the Kien Giang province. Also, the 2018 top 10 districts with the highest levels of salinity are all on the western part of the south coast of the Mekong Delta and the two island districts mentioned earlier. These districts already had very high levels of salinity in 2014 and only saw marginal changes in their salinity levels. Most districts that witnessed a very strong salinity increase in 2016 were located on the south coast of the Mekong Delta, located mainly in the Ben Tre and Tra Vinh provinces.

The following maps show soil salinity levels throughout the Mekong Delta in 2014, 2016 and 2018. It is clearly visible that the south coast, especially the eastern part of the south coast shows strong increases in salinity.

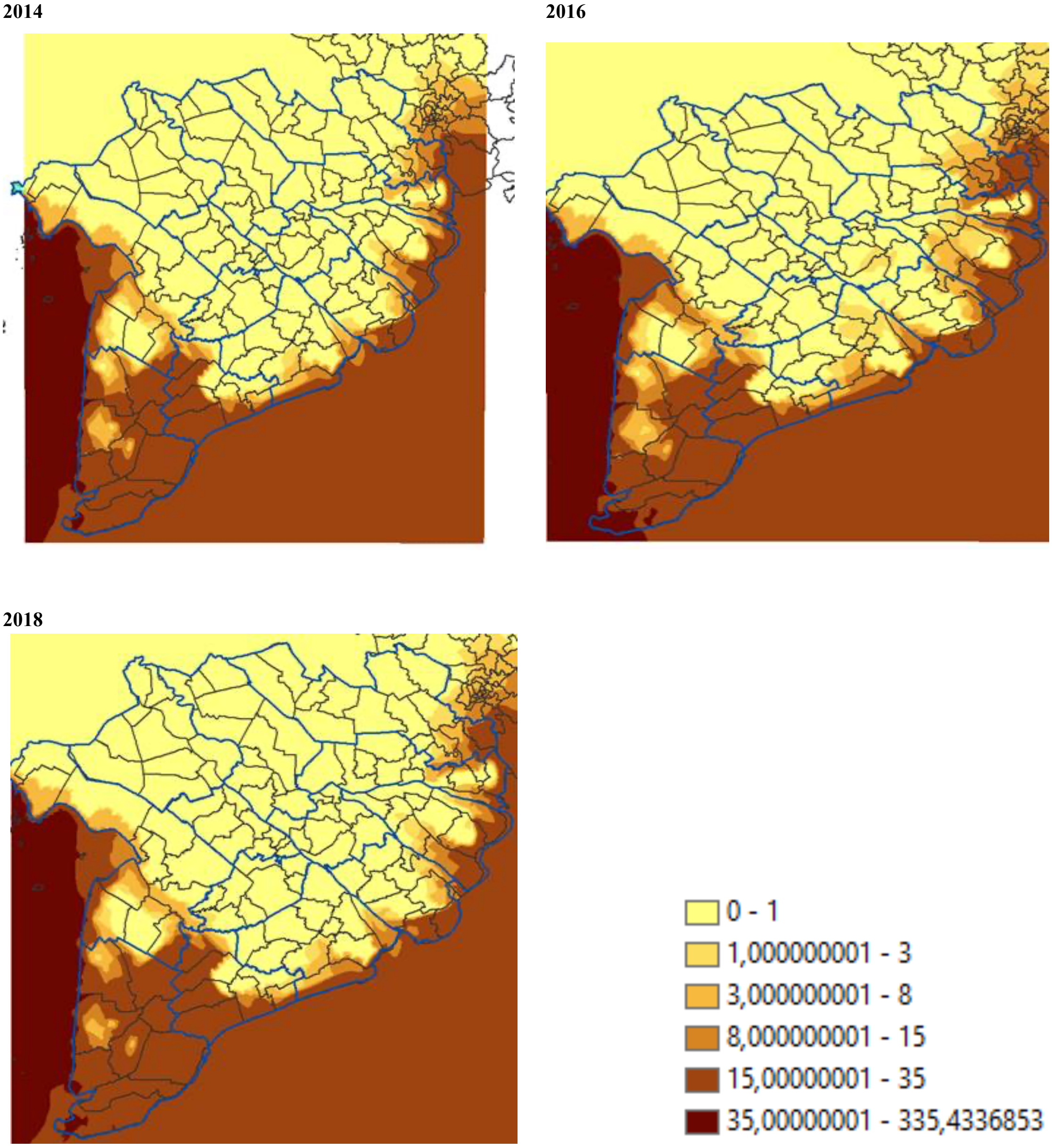

Figure 1. Soil salinity in the Mekong Delta

Exposure to salinity

Exposure to salinity is tested by looking at districts that saw a substantial increase in soil salinity and are near or already have a salinity level in 2014 that exceeds the FAO-threshold of 1.92 grams of chloride per litre of water. Of the 126 districts on which salinity data is available 80 have a soil salinity level of less than 1 gram per litre. The other 46 districts all had a salinity level of at least 1.6 gram per litre. In 2016, the number of districts that had a salinity level of at least 1.6 grams per litre jumped to 58. In 2018 it dropped back to 47, underscoring the temporal nature of the environmental shock.

At around 7.3 grams of chloride per litre of water, according to the FAO, rice will have lost a 100% if its yield. This suggests that districts that have a soil salinity level at 7.3 grams or higher will have a very small number of rice farmers. The 293 households in the panel that live in districts with a salinity level at 7.3 grams or higher, 126 (43%) still had revenue from rice. Of the 900 households that live in districts with a salinity level lower than 7.3 grams, 418 (46%) households had revenue from rice. 759 households live in districts with saline levels that have not yet reached the FAO-threshold. Of these households, 339 (45%) had revenue from rice. Of the 141 households that live in districts with salinity levels between 1.92 and 7.3, 79 (56%) of the households still cultivate rice.

Interestingly, land use and crop choice does not seem to be directly related to soil salinity levels. There is a higher share of households with revenue from rice cultivation in districts with a salinity level between 1.92 and 7.3 than in districts above or below that. A strikingly high share of households in districts with salinity levels above 7.3 still cultivate rice. A possible explanation for this could be that salinity level variation within district is large as a result of manmade dyke and sluice systems that is able to keep saltwater.

Looking at rice yields for each district might provide some clarification to these odd findings. For each district that had a soil salinity level of 1.6 grams or higher in 2014, 2016 or 2018 the winter-spring season rice yield per hectare was calculated for 2014, 2016 and 2018. As the VHLSS data does not cover the same group of households each year some districts have no observations of households that cultivate rice in a certain year. As a result, for 37 districts changes in salinity levels and average district rice yield from 2014 to 2016 and 30 districts for 2016 to 2018 are analysed.

No obvious relationship is visible between measured soil salinity and average rice yield in the VHLSS and salinity data. Between 2014 and 2016, a correlation coefficient of 0.0531 suggests a higher salinity level is accompanied by a slight increase in rice yield. Between 2016 and 2018, a negative correlation of 0.3311 was found, better fitting expectations of a negative relationship.

4.2 Empirical results & discussion

This paragraph is concerned with the statistical analysis of the data. The paragraph starts with static multivariate regression analysis on income levels of in each year and income changes between years. The second part of this paragraph is concerned with the panel analysis.

4.2.1 OLS

Household income

The next table shows the results of the initial regression where I investigate what the effects on income are of different household and commune characteristics. This is important because the first three regression columns only include household characteristics. The last three regression columns also include commune characteristics I use the natural logarithm of household income as the dependent variable to reduce the effect of outliers.

Table 9. OLS regression results household income

	2014	2016	2018	2014	2016	2018
	Log Income	Log Income	Log Income	Log Income	Log Income	Log Income
VARIABLES	1	2	3	4	5	6
Gender	0.0427	0.0476	0.135**	0.0722	0.0627	0.169**
Age	-0.00727***	-0.0101***	-0.0108***	-0.00883***	-0.0113***	-0.0124***
Education	0.0543***	0.0827***	0.0203***	0.0433***	0.0666***	0.0160**
Household size	0.252***	0.250***	0.247***	0.234***	0.238***	0.249***
Farm size	0.163***	0.234***	0.200***	0.163***	0.237***	0.204***
Non-farm labour	0.29***	0.234***	0.252***	0.329***	0.283***	0.259***
Agri income share	0.000843	-0.00538***	-0.00528***	0.00277***	-0.00338***	-0.00375***
Herfindahl index	-0.000473	0.00063	-0.00143	0.000033	0.000297	0.00224*
Road				0.198	-0.00284	0.0929
Central water				0.14*	0.168**	0.226***
Extension				0.113	0.133	0.114
Training				-0.123	-0.121	-0.263
Market distance				0.00913	-0.0157	-0.00298
Poor Percent					-0.0101***	
Constant	9.827***	10.47***	10.76***	9.545***	10.72***	10.57***
Observations	1,700	1,692	1,683	1,288	1,282	1,274
R-squared	0.322	0.357	0.35	0.339	0.366	0.362

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

As visible in the table above, the model has a very similar explanatory power in each year varying between an R-squared of 0.32 and 0.37. Commune characteristics add a fraction of explanatory power to the model with household characteristics. Slight changes in the effect and significance of some of the household characteristics are caused by adding commune characteristics but nothing worth mentioning specifically.

Household size and farm size both have a substantial effect on household income. An additional household member or an additional hectare of arable land, keeping all else constant, increases household income by 25 and 20 percent, respectively. Having at least one household member that does waged labour outside of agriculture tends to increase household income by more than 25 percent.

The explanatory variable Agri income share shows a shift in the profitability of agriculture before and after the environmental shock of late 2015 and early 2016. In 2014, a large share of agricultural income in the income mix of a household positively affected household income. In 2016 and 2018 this effect was negative.

Herfindahl index, which measures diversification, seems to have an insignificant effect in each year except in 2018 at the 10 percent level. Gender and the Herfindahl index are the only household characteristics that are primarily insignificant.

Of the commune characteristics only central water supply and the share of poor people living in the commune are significant. Both have an expected sign. Central water supply positively affects household income. The share of commune poor people is considerable as a one percent increase in it decreases household income by a little more than one percent.

Even though the availability of commune training facility insignificant each year it is still noteworthy that training is found to have a negative effect on household income in each year.

Household income change

The next regression table shows the results of the regressions with change in income as dependent variable. Household income change is modelled as relative change and actual change between 2014 -2016 and 2014-2018, adjusted for inflation.

Table 10. OLS regression results income change

Income	Relative change				Actual change			
	2016	2018	2016	2018	2016	2018	2016	2018
VARIABLES	1	2	3	4	5	6	7	8
Gender	-11.33	-7.416	-17.14	-8.116	-5894.1	-13616.5	-5847.5	-22073.1
Age	0.0304	-1.003**	0.106	-1.037*	-189.4	-785.6*	-221.1	-783.0
Education	2.742	0.200	2.321	-0.370	2401.6	474.1	920.9	151.2
Household Size	14.31***	21.46***	13.34***	22.81***	8775.1***	15345.8***	6603.4**	17384.4***
Farm size	10.29**	8.134*	10.68**	7.474	5660.7*	2862.2	5232.3	-85.07
Non-farm labour	34.17***	31.44***	35.56***	28.06**	11888.1*	3819.8	9893.0	-7966.3
2th income quartile	-81.48***	-112.9***	-84.39***	-117.1***	-11814.8	-8130.1	-10355.4	-6955.1
3th income quartile	-100.5***	-152.1***	-108.4***	-156.7***	-17161.9*	-18398.9	-17291.1*	-16558.1
4th income quartile	-130.9***	-176.0***	-136.6***	-171.5***	-50903.8***	-24054.3	-46657.4***	-4002.8
Agri income share	-0.0346	-0.0648	-0.0296	-0.0401	-166.6*	-96.71	-130.2	-93.93
Herfindahl index	-0.364**	-0.219	-0.386*	-0.188	-197.3	-173.0	-220.6	-263.5
Positive perception		58.07***		59.65**		40785.2*		41483.5
Exposure	-0.0693	2.785	-0.134	4.129	38.25	-18841.0	-11.69	-12141.9
Road			-42.32	27.42			5591.7	43037.9
Central water			29.25**	37.57**			13172.4	24145.6
Extension			18.56	21.42			12153.7	11830.3
Training			13.15	-14.91			13022.3	983.0
Market distance			-0.363	-0.925			-1577.6	-2357.2
Poor Percent			-0.946*				-452.2	
Constant	46.04*	90.78**	55.70	32.50	6062.8	2587.3	-14623.8	-57829.1
Observations	1668	1657	1271	1263	1668	1657	1271	1263
R-squared	0.136	0.158	0.139	0.148	0.050	0.024	0.42	0.029

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

The first two columns show the results of regressing household characteristics on the percentage change in income. The third and fourth column add commune characteristics to the regression of column one and two. The fifth and sixth column show the results of regressing household characteristics on the actual change in income. The last two columns add commune characteristics to the regressions of column five and six. More weight is put on the output of the first four regression columns as the explanatory power as given by the R-squared value is substantially higher than in the last four columns.

The income quartiles, perception and exposure are explanatory variables that were not used in the regressions of the previous section. The income quartile variables all refer to the base year of 2014 in order to see how being in a certain group based on income in the base year affects the adaptive capacity of a household. The first income quartile, containing the households with the lowest income, is the base category. The Agri income share and Herfindahl index also refer to values in the base year in order to see how diversification and focus on agriculture before the environmental shock affect household adaptive capacity.

Many of the explanatory variables that were also used in the regression of the previous section turn out to have a less significant effect on income change than on household income. Only household size and often non-farm wage remain significant at the one percent significance level. Farm size, agricultural income share and diversification are occasionally significant at the ten and five percent significance level. The signs of all significant explanatory variables remain the same for income change as they are for income. Central water supply and the share of commune poor households remain the only significant commune regressors.

Of the explanatory variables introduced in this section the income quartiles dummies and perception are significant in most regressions, especially with percentage change as dependent variable. All explanatory variables have signs as expected in most regressions except the income quartiles, the diversification index and exposure. The income quartile coefficients are all negative, suggesting that relatively richer households in 2014 have more trouble maintaining their income level. The diversification index has a negative and only occasionally significant effect on income change. Possibly, struggling households try many things to keep their income from decreasing. The effect of exposure varies between years and definition of the dependent variable. The varying effect of exposure suggests that salinity, in the form it is measured for this thesis, does not have a strong effect on income change, confirming what the descriptive statistics implied.

4.2.2 Logit

The dependent variable in the following table is a dummy that takes the value of one if the household had the same level of income or an increase in income between either 2014-2016 and 2014-2018, adjusted for inflation, and zero otherwise. The odds ratios columns add odds ratios for each coefficient for easier interpretation. The odds ratio of a variable is obtained by dividing the probability of the event by the probability of the non-event. The dependent variable with value one is the event, value zero is the non-event. In the model of this thesis, a unit increase in an explanatory variable increases the odds of maintaining a household's income level by the coefficient minus one, keeping all else constant. An odds ratio below one thus decreases the odds.

Table 11. Logit regression results income change

VARIABLES	2016 Income maintained 1	2016 Odds ratios 2	2018 Income maintained 3	2018 Odds ratios 4	2016 Income maintained 5	2016 Odds ratios 6	2018 Income maintained 7	2018 Odds ratios 8
Gender	-0.220	0.803	0.0113	1.011	-0.200	0.818	0.0338	1.034
Age	-0.0166***	0.984	-0.0255***	0.975	-0.0175**	0.983	-0.0227***	0.978
Education	0.0710*	1.074	0.0196	1.020	0.0357	1.036	0.0121	1.012
Household Size	0.317***	1.373	0.552***	1.737	0.288***	1.333	0.600***	1.821
Farm size	0.271***	1.312	0.250***	1.284	0.305***	1.357	0.232***	1.261
Non-farm labour	0.816***	2.261	1.113***	3.044	0.781***	2.184	1.141***	3.131
2th income quartile	-0.738***	0.478	-0.901***	0.406	-0.830***	0.436	-0.815***	0.443
3th income quartile	-1.270***	0.280	-1.844***	0.158	-1.321***	0.267	-1.818***	0.162
4th income quartile	-2.381***	0.093	-2.925***	0.054	-2.529***	0.080	-2.876***	0.056
Agri income share	-0.00375	0.996	-0.00395	0.996	-0.00369	0.996	-0.00414	0.996
Herfindahl index	-0.00583*	0.994	-0.00597*	0.995	-0.00576*	0.994	-0.00629	0.994
Positive perception			0.946***	2.576			0.818**	2.266
Exposure	0.00388	1.004	-0.400	0.670	0.00271	1.003	-0.481	0.618
Road					-0.297	0.743	0.143	1.153
Central water					0.119	1.126	0.300	1.350
Extension					0.164	1.178	-0.0885	0.915
Training					0.242	1.273	-0.208	0.812
Market distance					-0.0394	0.961	-0.00257	0.997
Poor Percent					-0.0213**	0.979		
Constant	0.686*	1.986	0.122	1.129	1.028	2.795	-0.193	0.824
Observations	1668		1657		1271		1263	
Pseudo R-squared	0.127		0.212		0.134		0.222	

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In this section the variable significance and effect are briefly discussed. Some first conclusions are drawn on the variables that do not reappear in the panel regressions. The third definition of income change that captures adaptive capacity in a straightforward way does not change much in terms of the signs and the effects of the explanatory variables. Age and farm size turn out more significant than under the first two definitions. Central water supply loses its significance. Only the share of commune poor households remains significant.

While education showed a strong, positive and significant effect on household income in each year, it loses its significance when regressed on income change in every case except one. Education even has a negative effect in one of the regressions, albeit insignificant. Household size and farm size both have a positive effect on the adaptive capacity of a household. Household size was significant at the one percent significance level except once. Farm size has been significant in most regressions. Having at least one household member that does waged labour has a very strong and almost always significant and positive effect on adaptive capacity.

The dummy variables for the income quartiles point to a negative relation between high income and adaptive capacity. Households in the lower income quantile had very high positive outliers. The highest one was an income increase of 20955 percent from 2014 to 2018.49 observations with the highest outliers were deleted for the analysis of income change. With these observations deleted, the effects of the income quartiles weakened but sign and significance remained unaltered. Only when using actual change as dependent variable the income quartiles are for the most part insignificant. Based on the other two dependent variable definitions and based on quantitative analysis hypothesis one is rejected.

The agricultural income share has been insignificant save one occasion at the 10 percent significance level and it has been negative in every regression. Diversification seems to have a negative effect on adaptive capacity but is often significant only at the 10 percent level. Perception, combined with non-farm labour, has the strongest positive and significant effect on the adaptive capacity of households. This is an interesting finding, as the descriptive statistics implied a lack of ability to perceive their adaptive capacity of households in the Mekong Delta. The sign of exposure varied between regressions and has been insignificant in each regression.

In every regression performed so far, commune extension and training availability and market distance have proven to be insignificant, meaning I cannot accept the fifth and sixth hypothesis. Market distance had, as expected, a negative coefficient in every regression concerned with income change. Extension and training had varying signs. A possible explanation for the insignificance and unstable sign of extension and training could be that the availability of extension services and trainings do not guarantee use of these services or training attendance. The data only contains information on in which communes training and extension service is offered.

4.2.3 Panel

In this paragraph I discuss the analysis of the panel of households that were surveyed in 2014, 2016 and 2018. I compare fixed effects and random effects to determine which model better fits the data. Because I have commune data observations for only one moment in time these variables are not included in this section. Time-invariant regressors drop out when using a fixed effects model. A fixed effects model, or within-groups regression model, uses variations about the means of explanatory variables to explain the variations about the mean of the dependent variable.

Table 12. Panel regression results income change

Income	Relative change		Actual change	
	Fixed effects	Random effects	Fixed effects	Random effects
VARIABLES	1	2	3	4
Gender	-22.147	44.426	16916.320	-9358.675
Age	2.211	4.193**	941.715	-177.073
Education	9.139	2.868	3817.860***	2561.405***
Household Size	107.930***	23.348*	24567.120***	10453.690***
Farm size	0.0003	-0.0006	1.180*	0.294
Non-farm labour	146.401*	68.239	21677.370*	5343.808
Agri income share	-4.030***	-0.104	-97.9215	-58.730
Herfindahl index	-2.139	-1.391*	-214.832	-209.767*
Exposure	0.462	0.0484	173.673	-2.394
Constant	-303.490	-250.432*	-147823.000**	1084.849
Observations	3346	3346	3423	3423
R-sq within	0.036	0.044	0.053	0.044
R-sq between	0.001	0.016	0.009	0.016
R-sq overall	0.001	0.022	0.016	0.022
Number of Id	1,697	1,718	1.718	1,718

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Three fixed effects and three random effects models using our three different definitions of the dependent variable have been performed. The results of the first two regressions use the Actual change in income as a dependent variable. The second two regressions use the percentage change in income as the dependent variable. The last two regressions use a dummy variable as the dependent variable, which takes the value of one if the income change was not negative and zero otherwise.

As is visible from the table above, the results show considerable differences in sign and significance between the fixed effects and random effects models while showing similarities between the two fixed effects models and the two random effects models. To determine which model best fits the data, I run a Hausman test on all Fe-Re combinations.

The test results for both the Actual and Percentage models show that I should use the fixed effects models in both cases. The models have the same number of explanatory variables, resulting in thirteen degrees of freedom. At eight degrees of freedom and the 1% significance level, the critical value of chi-squared is 20.09.

The Hausman test statistic for the *Actual* models is 39.38. For the *Percentage* models it is 50.81. The Hausman test for the binary dependent variable model is 65.76. For each test, this means I reject the null hypothesis that the unobserved effects are distributed independently of the variables of interest and use the fixed effects models for further analysis.

Table 13. Panel logit regression results income change

VARIABLES	Fe Income maintained 1	Re Odds ratios 2	Re Income maintained 3	Re Odds ratios 4
Gender	0.335	1.398	-0.247**	0.781
Age	0.034*	1.035	-0.009**	0.991
Education	0.076***	1.079	0.051***	1.052
Household Size	0.627***	1.872	0.148***	1.160
Farm size	0.00004**	1.000	0.00001	1.000
Non-farm labour	0.771***	2.162	0.602***	1.826
Agri income share	-0.005	0.996	-0.0001	0.999
Herfindahl index	-0.011***	0.989	-0.003*	0.997
Exposure	0.006	1.006	0.003	1.004
Observations	1786		3423	
Number of Id	893		1,718	

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In the table above the fixed effects logit model has a significantly lower amount of observations than the random effects model. The time period investigated limits this thesis to three observations per household. Every household that either had a decrease or increase in household income both between 2014-2016 and 2014-2018 drops out of the fixed effects model.

Using multiple observations for the same households over a period of time helps dealing with omitted variable bias as a result of unobserved heterogeneity. However, fixed effects regressions need variance in both the dependent variable and the independent variables. Education might change as the household head continues to study or because the household gets a new household head. But generally, a variable such as education stays level. The same goes for household size and farm size.

Almost every explanatory variable in the regressions of table 13 has a correlation coefficient of 0.6 or higher between observations in 2014, 2016 and 2018. Non-farm labour, the Herfindahl index and exposure are the only exceptions, the latter being the only one with almost no correlation between observations in 2016 and 2018. It seems that for successful panel analysis, either a longer period of time with more observations or other variables should be used. For this reason, in determining which hypothesis is accepted, static regression analysis will be leading, complemented by the findings of fixed effects regression.

Education has a positive effect on income in all panel regressions. It is also significant at the one percent significance level while being insignificant when using percentage change in income as the dependent variable. As expected, households with a higher education level seem to be better at maintaining their income level. However, education is often not or barely significant. For this reason, I cannot accept hypothesis four, that better educated farmers have a higher adaptive capacity to environmental change.

Household size seems to be the only explanatory variable that unequivocally has a positive and significant effect in each regression on household income change. Not taking the models with Actual change as its dependent variable into account, non-farm waged labour also has a positive and significant effect in each regression. Interestingly, not on a single occasion has household size been found to have a positive effect on the adaptive capacity. Non-farm income was mentioned once by Mariano (2012) to have a positive effect on adaptation.

Farm size was found to have a significant positive effect in almost every non-panel regression but had an often insignificant and neglectable effect in all panel regressions. Farm size had a correlation coefficient of 0.7 or higher between 2014-2016 and 2016-2018. Based on static regression I accept hypothesis two, that farmers with a large farm have a higher adaptive capacity to environmental change.

In accepting or rejecting the hypothesis on diversification I take three variables into consideration. The Herfindahl index, often significant at the ten percent significance level, has a negative effect on adaptive capacity. In the literature, diversification is often presented as an adaptive measure. As the available data did not include answers of respondents on whether they diversify as an adaptive measure diversification has been used as a regressor in maintaining an income level. It turns out to have a negative effect. An intuitive explanation is that households that notice or expect that their income is declining are likely to try everything they can to prevent this but fail to make these last resort attempts work.

When taking agricultural income share and non-farm waged labour into account I see that, as expected based on the descriptive statistics, non-farm waged labour positively affects adaptive capacity while having a high agricultural income share negatively affects it. Whether diversifying activities successfully helps in maintaining an income level seems to depend on what form of diversification is sought. As the Herfindahl index exists primarily of agricultural activities, it is no surprise that both the index and the agricultural income share have the same sign. Based on this dependence of the form of diversification I cannot accept hypothesis four, that farmers that have diversified their income sources have a higher adaptive capacity to environmental change.

Exposure turned out insignificant in every regression and varied widely between a positive and negative sign. Only exposure to salinity is measured, which means it does not capture many other environmental circumstances. Also, the variable measures change in soil salinity at commune level. As a result of sluice and dyke systems in the Mekong Delta, presumably, large differences in soil salinity levels within a commune can be found. This makes it hard to draw conclusions about the effect of exposure to soil salinity on adaptive capacity. Thus, the seventh and last hypothesis, that farmers less exposed to environmental pressure have a higher adaptive capacity to environmental change, cannot be accepted.

5. Conclusion

The adaptive capacity of farmers in the Mekong Delta has been researched extensively. Sustainable food production for Vietnam and surrounding countries gives rise to strong local interest in the Mekong Delta. Global concerns over climate change make the Mekong Delta an interesting study area of what rising sea levels will have in store for many other places on earth in the future.

Existing empirical literature that is concerned with the adaptive capacity of farmers under changing environmental circumstances mainly consists of focus group discussions followed by interviews with a relatively small group of farmers. The use of longitudinal farm data is predominantly found in developed countries where researchers have attempted to understand farm income dynamics. Research on adaptation at household level by analysing panel data is scarce.

This thesis attempts to explain which socioeconomic household and commune characteristics determine the adaptive capacity of farming households in the Mekong Delta using three sources. The main dataset is concerned with data at household level from which a panel was formed covering a five-year period. This was complemented by a dataset containing data on commune characteristics and a dataset containing soil salinity measures at commune level.

The research question:
To what extent do socio-economic community and farm-level conditions determine the adaptive capacity of Mekong Delta farmers under changing environmental circumstances?

On socioeconomic household characteristics, the results indicate clear positive effects of several characteristics such as farm size, household size, perception and non-farm waged labour on the adaptive capacity of a household. This thesis does not find evidence on the effects of other characteristics such as education, diversification and exposure to environmental pressure. One of the most striking findings is that a high household income at the beginning of the study period seems to negatively affect the adaptive capacity of a household. The finding of non-farm waged labour having a substantial and significant positive effect on the adaptive capacity has implications for food production in the Mekong Delta. If more households continue to shift their focus to waged labour outside of agriculture and climatic circumstances are deteriorating, it becomes increasingly difficult to make a living from farming. A substantial decrease in food production in the Mekong Delta could endanger food security in Vietnam and its neighbouring countries.

This thesis finds no conclusive evidence on the effects of various commune characteristics except the share of poor households in the commune, which negatively affects the adaptive capacity of households. This finding suggests that attempting to alleviate poverty in the poorest areas in the Mekong Delta offer greater benefits in term of adaptive capacity. However, this collides, to a certain extent, with the findings relating to hypothesis one, that a high household income negatively affects adaptive capacity. While the literature review showed strong positive effects of agricultural training and extension services, no evidence of those effects was found in the empirical results.

Soil salinity levels and how they changed between 2014 to 2018 in each district were not able explain much in terms of adding an environmental element to the thesis. With more households in areas with high soil salinity levels cultivating rice than in areas with low levels of salinity and an unstable sign and lack of significance in regression analysis, it seems this thesis failed to capture exposure to changing environmental circumstances. Information on household being located outside or inside a dyke area or salinity measures more specific than at district level, such as measures at commune level could help with this. Also, more elements that shape the biophysical environment should be taken into account, such as precipitation and temperature.

Besides extending research by adding more biophysical elements, future research concerning the adaptive capacity of farmers in the Mekong Delta or similar areas could be directed in other directions. The existing data can be used to focus on agricultural household income instead of full household income. By focussing on agricultural income, the impact of changes in environmental circumstances might be easier to explain by looking at changes in various crop yields and the effectiveness of inputs under different levels of environmental pressure.

The abundance of research that has investigated adaptation on a small scale and the lack of research using longitudinal data has made it hard to combine these two types of research. If I wish to know more about how various adaptive measures work out years after they have been put in place, and how perception, extension and education affects the success of these measures, an integrated approach might offer a solution. One of the main issues of this thesis has been defining different adaptive measures and subjective determinants of the success of these measures. Creating panels of the same households over a period of ten years or more that also captures specific adaptive measures, subjective determinants and biophysical circumstances will help developing our understanding of what drives the adaptation of farmers to changing environmental circumstances.

Bibliography

Arora, S. (2012). Farmers' Participation in Knowledge Circulation and the Promotion of Agroecological Methods in South India. *Journal of Sustainable Agriculture*, 207-235.

Arunrat, N., Wang, C., Pumijumnong, N., Sereenonchai, S., & Cai, W. (2017). Farmers' intention and decision to adapt to climate change: A case study in the Yom and Nan basins, Phichit province of Thailand. *Journal of Cleaner Production*, 143, 672-685.

Babatunde, R. O., & Qaim, M. (2009). Paterns of income diversification in rural Nigeria: determinants and impacts. *Quarterly Journal of International Agriculture*, 305-320.

Bank, W. (2016). *Transforming Vietnamese agriculture : gaining more from less.* Hanoi: World Bank.

Berhe, M., Hoag, D., Tesfay, G., Tadesse, T., Oniki, S., Kagatsume, M., & Keske, C. M. (2017). The effects of adaptation to climate change on income of households in rural Ethiopia. *Pastoralism*, 12.

Burnham, M., & Ma, Z. (2016). Linking smallholder farmer climate change adaptation decisions to development. *Climate and Development*, 289-311.

Burnham, M., & Ma, Z. (2017). Climate change adaptation: factors influencing Chinese smallholder farmers' perceived self-efficacy and adaptation intent. *Regional Environmental Change*, 171-186.

Can, N. D. (2016). Adaptation to salinity intrusion: an economic assessment of diversified farming systems in saline affected area of coastal Ben Tre Province of the Mekong Delta, Vietnam. *International symposium on current agricultural environmental issues in Pacific Rim nations and their countermeasures-II*, (pp. 15-26).

Dunn, J., & Williams, J. (2000). Farm characteristics that influence net farm income variability and losses. (p. 46). Vancouver: Ageconsearch.

Ersado, L. (2005). Income diversification before and after economic shocks: Evidence from urban and rural Zimbabwe. *Development South Africa*, 27-45.

Key, N., Prager, D., & Burns, C. (2017). *Farm Household Income Volatility: An Analysis Using Panel Data From a National Survey.* Washington: Economic Research Service.

Kibue, G. W., Liu, X. Z., zhang, X., Pan, G., Li, L., & Han, X. (2016). Farmers' Perceptions of Climate Variability and Factors Influencing Adaptation: Evidence from Anhui and Jiangsu, China. *Environmental Management*, 976-986.

Larson, C. (2016, April 6). Mekong megadrought erodes food security. *Science*.

le Dang, H., Li, E., Bruwer, J., & Nuberg, I. (2014). Farmers' perceptions of climate variability and barriers to adaptation: Lessons learned from an exploratory study in Vietnam. *Mitigation and Adaptation Strategies for Global Change*, 531-548.

Mariano, M. J., Villano, R., & Fleming, E. (2012). Factors influencing farmers' adoption of modern rice technologies and good management practices in the Philippines. *Agricultural Systems*, 41-53.

Minderhoud, P., Coumou, L., & Erkens, G. (2019). Mekong delta much lower than previously assumed in sea-level rise impact assessments. *Nature Communications*, 3847.

Nielsen, T., Keil, A., & Zeller, M. (2013). Assessing farmers' risk preferences and their determinants in a marginal upland area of Vietnam: A comparison of multiple elicitation techniques. *Agricultural Economics (United Kingdom)*, 255-273.

Organization, F. a. (2017). *A flora of agricultural and horticultural crops.* Wageningen: United Nations.

Phimister, E., Roberts, D., & Gilbert, A. (2005). The Dynamics of Farm Incomes: Panel data analysis using the Farm Accounts Survey. *Journal of Agricultural Economics*, 197-220.

Phuong, L. T., Biesbroek, G. R., Sen, L. T., & Wals, A. E. (2018). Understanding smallholder farmers' capacity to respond to climate change in a coastal community in Central Vietnam. *Climate and Development*, 701-716.

Schad, I., Schmitter, P., Saint-Macaray, C., Neef, A., Lamers, M., Nguyen, L., . . . Hoffmann, V. (2012). Why do people not learn from flood disasters? Evidence from Vietnam's northwestern mountains. *Natural Hazards*, 221-241.

Schmitt, R. J., Bizzi, S., Castelletti, A., Opperman, J. J., & Kondolf, G. M. (2019). Planning dam portfolios for low sediment trapping shows limits for sustainable hydropower in the Mekong. *Science Advances*.

Singh, C., Dorward, P., & Osbahr, H. (2016). Developing a holistic approach to the analysis of farmer decision-making: Implications for adaptation policy and practice in developing countries. *Land Use Policy*, 329-343.

Smajgl, A., Toan, T. Q., Nhan, D. K., Ward, J., Trung, N. H., Tri, L. Q., . . . Vu, P. T. (2015). Responding to rising sea levels in the Mekong Delta. *Nature Climate Change*, 167-174.

Smit, B., & Wandel, J. (2006). Adaptation, adaptive capacity and vulnerability. *Global Environmental Change*, 282-292.

Tien Dung, L., Phi Ho, D., Thi Kim Hiep, N., & Thi Hoi, P. (2018). The Determinants of Rice Farmers' Adoption of Sustainable Agricultural Technologies in the Mekong Delta, Vietnam. *Applied Economics Journal*, 55-69.

Tran, T. A., Nguyen, T. H., & Vo, T. T. (2019). Adaptation to flood and salinity environments in the Vietnamese Mekong Delta: Empirical analysis of farmer-led innovations. *Agricultural Water Management*, 89-97.