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Reported weather shocks and rural household welfare: Evidence from panel data in Northeast Thailand and Central Vietnam

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ABSTRACT

Extreme weather events are reported to have severe effects on rural households in the developing world. This study uses a unique and comparable panel dataset of about 4000 rural households collected in three years (2010, 2013, and 2016) from Northeast Thailand and Central Vietnam to examine and compare the welfare effects of floods, droughts, and storms reported to be experienced by rural households. Our results show that these weather shocks have significant effects on household income, consumption, and poverty in both countries, though the levels of severity are different. Drought is the common extreme weather event in these two countries with significant and negative effects on household income, consumption and poverty. In Thailand, floods have higher impacts on rural households in terms of income and poverty than storms do. Compared to Thailand, Vietnam is more exposed and significantly affected by storms. In addition to weather shocks, the welfare of rural households is significantly affected by other factors representing their livelihood platforms. Promoting farm mechanization and rural education should be given high priority in both countries. In Thailand, the accumulation of farmland should also be encouraged. In Vietnam, accelerating internet access and supporting livestock production would contribute to increasing household income and consumption and consequently decreasing poverty.

1. Introduction

Extreme weather events such as floods, droughts and storms are reported to have severe effects on rural households in the developing world (Mera, 2018; Reynaud et al., 2018; Twongyirwe et al., 2019; Halkos and Skouloudis, 2020; Zhang and Managi, 2020). Over time, floods and storms have become stronger and more frequent, while droughts are longer and more intense (UN-HABITAT, 2011; Amare et al., 2018). In addition, almost all countries with high numbers of extreme weather events and victims are categorized as low or lower-middle income countries (Miyan, 2015). The Intergovernmental Panel on Climate Change (IPCC, 2012) reports that, in the period from 1970 to 2008, more than 95% of fatal victims related to weather disasters were in those developing countries. Rural households in developing countries are especially vulnerable to extreme weather events for several reasons (Shiferaw et al., 2014). First, they are highly dependent on weather-sensitive sectors such as agriculture (Kurosaki, 2014; Dube and Sivakumar, 2015). Second, their welfare levels are low and their coping capacity to deal with weather shocks is inadequate (Shehu and Sidique, 2014; Lohmann and Lechtenfeld, 2015). Third, in these countries the institutional arrangement and warning systems for extreme weather events are often absent (Heltberg et al., 2009; Nguyen and Nguyen, 2020).

Increasing extreme weather events seem to be a global phenomenon but their effects are locally different due to different levels of exposures and coping capacities at both national and household levels (Nguyen and Tenhunen, 2013; Khanal et al., 2017). At the national level, the relative impacts of weather shocks on the economy tend to be larger in less developed countries. At the household level, rural households are more vulnerable. Thus, assessing local economic impacts of extreme weather events on rural households provides useful information when it comes to developing effective public programs and interventions aimed at mitigating the negative impacts (Dercon et al., 2005).

In the current literature, the exposure of rural households to extreme weather events are measured with two major approaches (Rajapaksa et al., 2016; Nguyen and Nguyen, 2020). The first one is to trace the

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times and places where the shocks happened and to match them with the locations of the surveyed households (Dell et al., 2014). Measured weather shocks are exogenous, but subject to basis risks. For example, a weather shock hits a community, but the typography is not homogeneous enough to ensure that all households within this community are actually affected. The heterogeneity in local typography leads to some specific areas being affected while other areas in the same community are not. The second approach is to ask the surveyed households to report if they have experienced any weather shocks. Since the former approach is not always feasible, especially in developing countries because long-term weather data at the local level in developing countries are not available, the latter approach has been widely used in rural household surveys (Heltberg et al., 2015; Nguyen and Nguyen, 2020). This approach helps to avoid the basis risk problems as information about shocks is collected at the household level and reflects household's vulnerability and resilience. However, data reporting could suffer from reporting biases. Failure to report a weather shock can be due to the coping capacity as well as risk perception of households (Nguyen and Nguyen, 2020). In addition, households may mislead between regular climate events, which are predictable and even can benefit households (e.g. regular flooding), and actual weather shocks. Furthermore, reporting errors may come from the length of the recall period on reporting of shock events (Nguyen et al., 2020a). After a long period of time with different events, households cannot correctly recall all events occurred, the severity, the damage and the coping strategies they used in response to these events.

There is a growing theoretical and empirical literature on the impacts of weather shocks in developing countries using household survey data (Ersado et al., 2003; Harrower and Hoddinott, 2005; Kim and Prskawetz, 2009; Berloffa and Modena, 2013; Kurosaki, 2014; Rakib and Matz, 2016; Rigg et al., 2016; Khanal et al., 2017). However, most studies refer to only a single country, making it difficult to compare the impacts between countries because different studies use different definitions or different survey methods. Comparing the effects of weather shocks on rural households between countries offers a functioning instrument to enhance our understanding of the effects of weather shocks, since one country can benefit from the experiences of another. One of the challenges in this regard is the lack of comprehensive and comparable data at the household level in different countries. Hence, our study contributes to filling this gap by employing a large-scale panel household and village dataset from three provinces in Northeast Thailand and three provinces in Central Vietnam collected in 2010, 2013 and 2016. The panel dataset is harmonized, as the same questions have been asked and the same survey method has been used. Specifically, we would like to examine and compare the effects of three major types of weather shocks, namely storms, droughts, and floods, on household income, consumption and poverty in these two developing countries as these weather shocks are reported to be the most common and severe in these two countries.

We choose Thailand and Vietnam as our study sites because of several reasons. These two developing countries are located in the Asia-Pacific region, which is considered the most affected region by weather shocks all over the world, not only in terms of the number of people affected but also in terms of the number of extreme weather events (). In 2015, nearly half of the world's weather disasters occurred in this region, affecting about 59.3 million people and causing a total damage of US$ 45.1 billion (UNESCAP, 2016). Vietnam and Thailand are reported to be among the most ten affected countries in the last two decades with Vietnam being ranked at 6th place and Thailand at 8th place (Eckstein et al., 2020). In addition, these two countries also share some other common characteristics. Both are emerging economies with high economic growth rates but have high labor proportions engaging in the agricultural sector (World Bank, 2017a). There are millions of smallholder farmers in these two countries and their income comes mainly from agricultural production (Rigg et al., 2016; Nguyen et al., 2017). However, Thailand and Vietnam are also different in several aspects. Thailand is an upper-middle income country with the Gross National Income (GNI) per capita of US$ 16,070 PPP (Purchasing Power Parity) in 2016. The agricultural sector contributes only 8% to the Gross Domestic Product (GDP) but accounts for about 32% of total employment (World Bank, 2017a). According to the Human Development Report of the United Nations Development Program (UNDP, 2016a), Thailand ranks 87 out of 188 countries and belongs to the high human development category with a Human Development Index (HDI) of 0.74. Vietnam is a lower middle-income country and is less economically developed than Thailand. In 2016 Vietnam had a GNI per capita of US$ 6050 PPP. It means that the income of a Vietnamese is equivalent to 38% of the income of a Thai (World Bank, 2017a). The agricultural sector of Vietnam contributes 18% to the GDP but accounts for 44% of total employment (World Bank, 2017b). Moreover, Vietnam's HDI is only 0.68, which puts it into rank 115 worldwide of the medium human development category (UNDP, 2016b). In this regard, our findings are relevant to other rapidly developing economies.

The rest of the paper is structured as follows. Section 2 reviews previous studies on the welfare effects of weather shocks using household survey data. Section 3 describes the study design and the empirical strategy. Section 4 presents the results and discusses the findings. Section 5 summarizes and concludes.

2. Literature review

Shocks are defined by Dercon et al. (2005) as adverse events which cause losses in income, assets or consumption of households. They can be divided into many categories, such as economic, health, weather, political, social shock or crime. The most common shocks to rural households in developing countries include health shocks (illnesses or deaths of household members) (Nguyen et al., 2020b) and weather shocks (Lohmann and Lechtenfeld, 2015). This paper focuses only on weather shocks that are reported by rural households. Their impacts can be found in many aspects of livelihoods and have been extensively documented, especially in rural areas. For example, rural Russia experienced in 2010 the worst drought since 130 years. It affected millions of acres of wheat, leading to an increase in wheat prices all over the world (Kramer, 2010). Also floods and storms can have very severe effects as they can destroy crops of rural households and the basic infrastructure of a country, including buildings, roads, telecommunication, water and electricity supply. For example, the physical infrastructure of Haiti was severely devastated after the occurrences of four storms in 2008 (Guha-Sapir et al., 2016). Hoddinott and Kinsey (2001) and Alderman et al. (2006) also report that floods are persistent and related to reduced growth of income and human capital in the long-term. Even worse, a weather shock can be a cause of poverty (Dercon et al., 2005; Lohmann and Lechtenfeld, 2015).

In the literature, many studies have evaluated the effects of weather shocks reported by rural households in rural household surveys. One of the advantages of using reported weather shocks is that they can be linked to the coping capacity of affected households. Employing a cross-sectional dataset of the National Income Consumption and Expenditure Survey in Zimbabwe in the early 1990s, Ersado et al. (2003) show that rainfall shocks have significant and negative impacts on household consumption. Kim and Prskawetz (2009) use panel data of the Indonesian Family Life Survey and find that weather shocks have significant and positive impacts on household consumption. The authors explain this surprising finding through a "timing effect" that the consumption decreases immediately after the shocks and increases again when the coping strategies are applied. This result indicates that the coping mechanisms of households in Indonesia are efficient, even overcompensating the damages of weather shocks. Dercon et al. (2005) use the Ethiopian Rural Household Survey data from 1999 to 2004 to examine the impact of weather shocks on rural household consumption. Their results show that drought is the most common shock reported by more than half of the households, while flood is reported by only 17% of the households. While droughts have significant and negative impacts on rural household consumption, floods do not have any significant impacts. Porter (2012) also uses the Ethiopian Rural Household Survey data collected from 1994 to 2004 to estimate the impact of weather shocks and concludes that rural household consumption is significantly reduced by rainfall shocks. Kurosaki (2014) uses panel data collected in 2001 and 2004 to examine the impacts of floods and droughts on household consumption in rural Pakistan. He reports that while floods have significant and negative impacts on consumption, the impact of droughts is insignificant. He argues that rural households in Pakistan may have established some institutions to lessen the damages of droughts, since they occur more frequently than floods. Shehu and Sidique (2014) use a nationally representative survey of rural households in Nigeria in 2010–2011 and find that weather shocks do not have any significant effect on non-poor households, while they decrease significantly consumption of poor households.

Regarding our study sites, Garbero and Muttarak (2013) use data from the National Rural Development Committee Survey and the Basic Minimum Need Survey to examine the impacts of the worst droughts and floods occurring in Thailand in 2010 on community welfare. They find that these extreme weather events do not decrease significantly food and non-food consumption expenditures of the rural households. This finding indicates that rural communities in Thailand are able to smooth their consumption after the occurrences of weather shocks. This is consistent with Lertamphainont and Sparrow (2016) who report that Thai farming households are able to smooth consumption in responses to floods and droughts. However, landless households are more vulnerable to weather shocks, indicating that the impacts of weather shocks also depend on household characteristics. It is noted that these studies use only cross-sectional household data. In Vietnam, some empirical studies using household survey data on the impacts of weather shocks are from Bui et al. (2014) and Arouri et al. (2015). They both employ the Vietnam Household Living Standard Survey to examine the impacts of natural disasters on different aspects of household welfare in Vietnam. The natural disasters can be droughts, storms, floods, or tornados. Their empirical results are similar and reveal that natural disasters decrease significantly household income and expenditure. Lohmann and Lechtenfeld (2015) use data from rural households and find similar evidence.

In summary, the results of the above studies on the impacts of weather shocks on rural household income and consumption are inconclusive as some of them have significant effects while others do not. In addition, rural households in some countries are capable of coping with some extreme weather events, while that is not the case in other countries. In other words, the impacts of weather shocks depend not only on the particular type of shocks but also on many other household and community characteristics. Moreover, all of the above studies are from a single country. Our paper thus extends the literature by comparing the effects of major weather shocks (storms, floods, droughts) on rural households in Thailand and Vietnam.

3. Study design

3.1. Data collection

We use the data from a longitudinal survey under the research project "Poverty dynamics and sustainable development: A long-term panel project in Thailand and Vietnam".[1] The project aims to examine and compare economic dynamics and vulnerability of rural households to poverty in these two emerging economies (Klasen and Waibel, 2015). Three provinces in Thailand (Buri Ram, Nakhon Phanom, Ubon Ratchathani) and three provinces in Vietnam (Dak Lak, Ha Tinh, Thua Thien Hue) were chosen as study sites (Fig. 1) because these provinces are rural and exposed to many extreme weather events. Dak Lak and Ha Tinh are in the central coast of Vietnam, having a border with Laos in the west and a long coast in the east. Meanwhile, Dak Lak is located in the Central Highland region and has a border with Cambodia in the west and is the most important coffee producing region of Vietnam. With a population density of less than 150 people/km^2, Dak Lak is less populated than the other two provinces (GSO, 2020). In addition, it has a very high level of ethnic minorities, whereas population in Ha Tinh and Hue is more homogenous with only a small share of ethnic minorities. Regarding economic conditions, these provinces are commonly characterized by a high incidence of poverty and a high dependence on agriculture. The three provinces in Thailand (Buri Ram, Nakhon Phanom, and Ubon Ratchathani) are located in the Northeast, sharing a border with Cambodia in the east and accounting for a third of the country's population and a third of its area. However, these provinces are among the least developed provinces in Thailand with about 40% of Thailand's poor residing there (Bird et al., 2011). The economy mainly depends on agriculture, especially on rice production. More than 60% of all rural households in the Northeast region are involved in rice production and more than two thirds of land area are used for rice cultivation (Suebpongsang et al., 2020).

The sampling procedure includes three stages following the guidelines of the United Nations Department of Economics and Social Affairs (UN, 2005) and is described in Nguyen et al. (2017). At the first and second stages, sampled sub-districts/communes and then sampled villages were selected based on the size of the human population. At the third stage, ten households in each sampled village were randomly chosen with equal probability. The total number of sampled households for each survey wave was about 2200 in 220 villages in each country.

The surveys were conducted by researchers from the Leibniz University Hannover and the University of Göttingen (Germany) in collaboration with various local institutions in these two countries, including the University of Ubon Ratchathani in Thailand, Hue University and Institute for Policy and Strategy for Agriculture and Rural Development in Vietnam. Before the surveys took place, all enumerators were carefully selected and intensively trained. Field operations were conducted by teams of five to ten enumerators managed by a team leader. Each enumerator was assigned to interview a number of households in an accidental manner (Phung et al., 2015). Each interview took, on average, two hours and was conducted at households' homes. After the interview, each completed questionnaire was first cross-checked for plausibility and consistency by another enumerator. In case of incomplete or inconsistent information, the responsible enumerator had to collect the information again, either by another visit to the household or by phoneNguyen et al., 2020b. At the end of the day, the questionnaire was again checked by the team leaders. The data was passed on for the data entry process only when the questionnaire was complete. Data entry took place at the field team's base and partially helped detecting implausible information and missing cases (Nguyen et al., 2020b). If there was a problem with the data, they were sent back again to the enumerators. In addition, during the data collection process, there were free days for all enumerators to catch up with all the checking.

Two survey instruments were used for data collection: the household questionnaire for household heads and the village questionnaire for village officials. The village questionnaire records information on the economy of the village such as the physical accessibility to the village and the share of households having internet access. The household questionnaire contains different sections. Section 1 documents administrative information. Section 2 comprises the demographic information of the households, including information of each household member regarding education and health. Section 3 is about shocks. Section 4, 5 and 6 are on different income generating activities of the households (farming, natural resource extraction, off-farm wage employment and non-farm self-employment). Section 7 is on borrowing, lending, public

[1] For more information see https://www.tvsep.de/overview-tvsep.html, household and village questionnaires are available for free download from this page.

Fig. 1. Study sites in Northeast Thailand and Central Vietnam.

transfers, taxation and insurance. Section 8 is on household expenditures. Section 9 is on household assets. More specifically, section 3 lists all shocks that the household has experienced and then 11 questions are asked for each shock event, which address its type, time of occurrence, which household member is affected, estimated severity, and total losses in income, consumption or assets. To prevent these reporting biases, the enumerators were trained to clarify with the surveyed households that an event which is considered a shock is only when it causes damages and losses to household income, household assets or leads to extra expenditure. In addition, during the data cleaning process, all shock events which cause no impact or cause no damages or losses to households were excluded. We use the data collected in 2010, 2013, and 2016. We exclude the households with missing information on important variables of our interest. Thus, the sample size for our analysis includes 5809 observations from Vietnam and 5833 observations from Thailand.

3.2. Data analysis

3.2.1. Identifying dependent variables

When analyzing the impacts of weather shocks on rural households' welfare, many authors use either household consumption or household income data as the dependent variable representing the household welfare (Dercon et al., 2005; Kim and Prskawetz, 2009; Porter, 2012; Garbero and Muttarak, 2013; Kurosaki, 2014; Bui et al., 2014; Arouri et al., 2015). Some authors argue that household consumption is more appropriate than income when examining the impacts of weather shocks because consumption is more closely related to the household well-being, since income refers to intermittent earnings of the households, while consumption is smoothed over time (O'Donnell et al., 2007). Other authors have a different view, declaring that income reflects household welfare in the short run, whereas consumption reflects household welfare in the long run (Haughton and Khandker, 2009). In addition, consumption data is less sensitive to weather shocks for the poor, as their consumption is mainly for basic needs such as food, water and shelter, and their consumption is already at a very low level. Therefore, for surviving, in times of hardships, they are more likely to adopt coping strategies to smooth their consumption rather than substantially cutting back their consumption for basic needs.

With regard to poverty, both non-monetary and monetary indicators are used to measure poverty. However, monetary indicators such as household income or consumption are more commonly used as this information is easier to collect and is available in most household living standard surveys. In addition, these monetary indicators could well reflect a household's ability to meet critical basic needs in food, clothing and shelter (World Bank, 2018). Furthermore, an advantage of monetary indicators is that it could be used to illustrate changes over time and to compare living standards between countries. However, income and consumption data might suffer from reporting bias. Households may be reluctant to disclose the full extent of their income or to report income earned illegally (Parvathi and Nguyen, 2018), or because of the large number of different expenditures involved, they cannot remember correctly how much they did consume on each item (Cameron and Worswick, 2001). In recent years, some studies have used non-monetary indicators such as the multidimensional poverty index. The main advantage of this approach is that it captures other dimensions of household well-being such as education, health and access to basic infrastructure and services (water, sanitation and electricity). However, the multidimensional poverty index does have some drawbacks, mainly due to data constraints. First, the index is constructed from numerous dimensions, but information of relevant items is not always available in household living standard surveys. Second, the index may not reflect capabilities but instead outputs (such as years of schooling) and inputs (such as cooking fuel). Last, the selection of dimensions and indicators, and the choice of indicators' weights and of the poverty cut-off are still being debated (UNDP, 2019).

In this paper we use both income and consumption as welfare indicators or livelihood outcomes in order to examine the impacts of weather shocks. This also allows us to cross-check our results because there might be measurement errors in measuring household income and consumption (Cameron and Worswick, 2001; Parvathi and Nguyen, 2018; Do et al., 2019). Household income includes farm income and non-farm income. Farm income derives from crop and livestock production, and non-farm income from off-farm wage employment and self-employment. As household income could be negative due to income losses, we use the absolute values of these income indicators. Household consumption includes food consumption and non-food consumption. Food consumption consists of expenditures for purchased food and the value of self-produced food. Non-food consumption includes expenditures for personal care, transportation, communication, health, education and social activities. As consumption data are positive, they are transformed into the logarithmic form in order to symmetrize the residuals and to reduce potential outliers in value. These income and consumption variables are identified per capita at the household level. To determine whether a household is in poverty, we use the threshold value of 1.9 PPP US$/day of per capita income or per capita consumption. Thus, our dependent variables include per capita household income, per capita household farm income, per capita household non-farm income, per capita household consumption, per capita household food consumption, per capita household non-food consumption, and the household poverty status.

3.2.2. *Identifying weather shock variables and other independent variables*

The identification of explanatory variables for the regression models is based on the sustainable livelihoods framework, whereas a livelihood is defined as the capabilities, assets, and activities of a means of living (Ashley and Carney, 1999; Ellis, 2000). This framework includes livelihood platforms, livelihood strategies, and livelihood outcomes (Fig. 2). The livelihood platforms with different types of capital are the basis for a household to choose its livelihood strategies such as agricultural production (e.g., crop and livestock) and/or non-farm/off-farm employment under specific local physical (e.g. weather conditions) and socio-economic environments. The selected livelihood strategies lead to a set of livelihood outcomes with regard to income or consumption. Thus, the factors affecting household welfare (income, consumption, and poverty) theoretically include income shocks (e.g. weather shocks or health shocks), physical and socio-economic conditions of the living environment (e.g. village characteristics), and the household livelihood platforms (natural, physical, human, financial, and social capital). These are independent variables.

With regard to the shocks faced by rural households, we use weather shocks and health shocks as these are the most severe income shocks to rural households in developing countries (Heltberg et al., 2015). Weather shocks include storms, floods, and droughts as they are the most common extreme weather events in Vietnam and Thailand (Nguyen et al., 2017). We use the number of storms, floods and droughts reported by farmers as our independent variables. As a storm can also lead to a flood, we ignore the storm-induced flood events in the number of floods. Health shocks include the sicknesses or deaths of household members. To represent the local conditions, we use two variables at the village level. The first one is a dummy to indicate whether the village is accessible during the whole year with motorbikes. The second one is the share of the households in the village with internet access at home. At the household level, natural capital is represented by the landholding of the household as it is the main productive asset in rural areas of developing countries (Nguyen et al., 2015). Physical capital includes monetary value of livestock, the number of tractors, and the number of motorbikes (the main mode of transport in these provinces). Human capital is represented by household size, share of working-age members in the household, education level, age and gender of the household head who is the final decision-maker in the household. Financial capital is

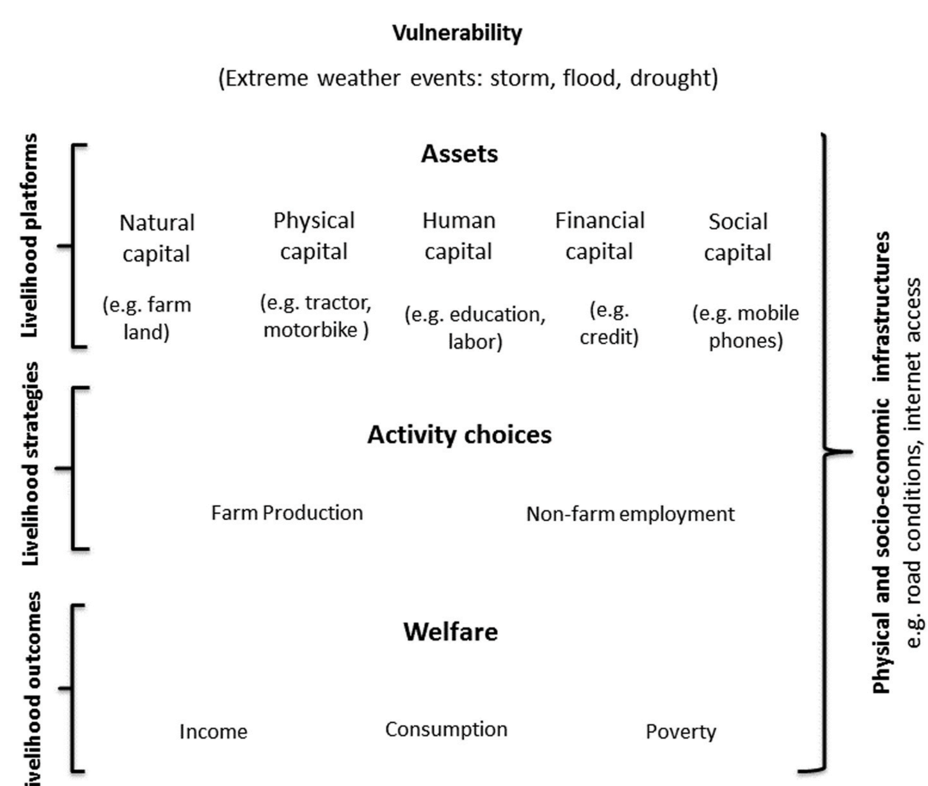

Fig. 2. The sustainable livelihoods framework (modified from Ashley and Carney, 1999; Ellis, 2000; Nguyen et al., 2015).

represented by the amount of loans and social capital is represented by the number of phones used by all household members, including mobile phones. In addition, we also include the time dummies for other factors that are time-variant during the study period 2010 to 2016. These variables are described in Table 1.

3.2.3. Specification of econometric models

We use econometric regressions to estimate the effects of independent variables including weather shocks on dependent variables (welfare outcome variables). From the livelihood framework presented above, the basic form of the econometric model is:

$$Y = f(S,\ H,\ V) \tag{1}$$

where Y is the outcome (dependent) variables (described in section 3.2.1), S is a vector representing the shocks that the household faced, H is a vector representing the household characteristics (livelihood platforms), and V is a vector representing physical and socio-economic conditions of the village (described in section 3.2.2).

There are several econometric challenges that need to be taken into account. First, since we have panel data (2010, 2013, and 2016), either fixed effects or random effects regressions can be chosen. We performed Hausman tests and the results reveal that a fixed effects regression is the appropriate specification (see the results of Hausman tests in Annex 1). Second, there might be an endogeneity problem because the variables of reported shocks can be correlated with the household and village characteristics that are not observable. These unobserved variables can be decomposed into time-variant and time-invariant variables. Thus, we use a fixed effects regression to eliminate time-invariant variables. Since weather shocks are covariate shocks and are more likely to be correlated with unobserved village characteristics, we use fixed effects regression at the village level to account for this problem (see Arouri et al., 2015). Third, because the number of explanatory variables is high, we conducted the Variance Inflation Factor (VIF) test to detect a potential perfect multicollinearity problem. The results of VIF tests reject this problem (see the results in Annex 2). Finally, to control for econometric heteroscedasticity, the standard errors are also clustered at the village level. Thus, the model is further specified as follows:

$$Y_{ijt} = f(\beta_1 + \beta_2 H_{ijt} + \beta_3 S_{ijt} + \beta_4 V_{it} + \beta_5 T_{ij}) + \varepsilon_j + \tau_{ijt} \tag{2}$$

where Y_{ijt} is a welfare indicator of household *i* in village *j* in the year *t*; H is a vector capturing household livelihood assets; S is a vector representing the shocks faced by household *i*, including weather shocks and health shocks; V is a vector representing physical and socio-economic conditions of the village; T is dummy variables of years; ε is the village fixed effects and τ is the error term.

Table 1
Independent variables in the regression models.

Variables	Scale	Definition
storm	Metric, number	No. of storms household faced during the last 12 months
flood	Metric, number	No. of floods household faced during the last 12 months
drought	Metric, number	No. of droughts household faced during the last 12 months
sick	Metric, number	No. of sicknesses or deaths of household members during the last 12 months
farmland	Metric, ha	Farm land area of household
livestock	1000 PPP US$	Value of household livestock
phone	Metric, number	Number of phones household members use
borrow	1000 PPP US$	Value of loan household borrowed during the last 12 months
motorbike	Metric, number	Number of motorbikes household has
tractor	Metric, number	Number of tractors household has
family_size	Metric, person	Number of household members
male_head	Dummy (1 = yes)	Household head is male
age_head	Metric, years	Age of household head
ethnic minority	Dummy (1 = yes)	Household belongs to ethnic minority groups
farmers	Dummy (1 = yes)	Farming is the main occupation of the household
school_head	Metric, years	Number of schooling years of household head
labor_share	Metric, percentage	Share of household members with age of 15–64 years
internet_village	Metric, percentage	Share of households having internet access at home in the village
road_village	Dummy (1 = yes)	Village is accessible all year around with motorbikes
2010	Dummy (1 = yes)	Survey year is 2010
2013	Dummy (1 = yes)	Survey year is 2013

PPP US$ in 2005.

4. Results and discussion

4.1. Weather shocks and household characteristics

Fig. 3 indicates the proportion of households reporting weather shocks in the reference period. Drought is the most common weather shock in both countries, affecting about 20% of the surveyed households in rural Northeast Thailand and about 15% of the surveyed households in rural Central Vietnam. This might be due to the fact that the irrigation system in the study sites is better in Vietnam than in Thailand (see Phung et al., 2015). Flood is the second common weather shock reported in both countries, which affects about 5% of the surveyed households in Thailand and 7% of the surveyed households in Vietnam. These numbers are 2% and 7% for storms, respectively. This means rural households in Vietnam experience more floods and storms than their Thai fellows do. This is in line with Lohmann and Lechtenfeld (2015) who argue that Vietnam is especially prone to floods and storms due to its long coastline.

Fig. 4 reports the average loss of each weather shock event. It shows that (i) each weather shock event brings a large loss to rural households in terms of income, consumption, or assets; and that (ii) the severity is different between flood, drought, and storm events in these two countries. In Vietnam, the most severe weather shock in terms of income, consumption and asset losses is storm, followed by drought and then by flood. This order for Thailand is flood, drought, and storm. Thus, flood is the most severe weather shock in Thailand but the least severe in Vietnam. This is probably due to the availability of rural irrigation systems. The irrigation system is better in Vietnam than in Thailand, and thus it

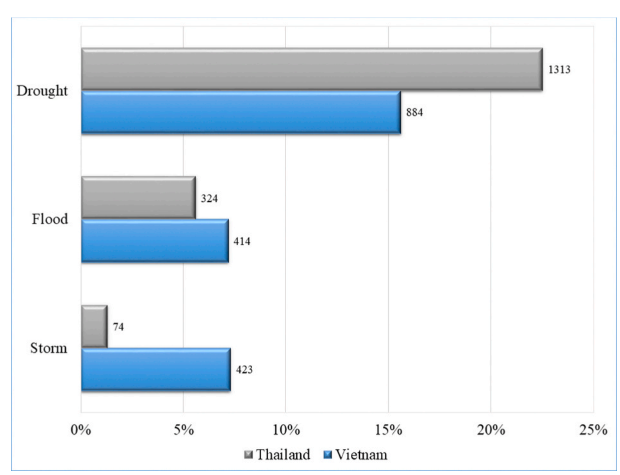

Fig. 3. Share of survey households reported to be affected by weather shocks (%).

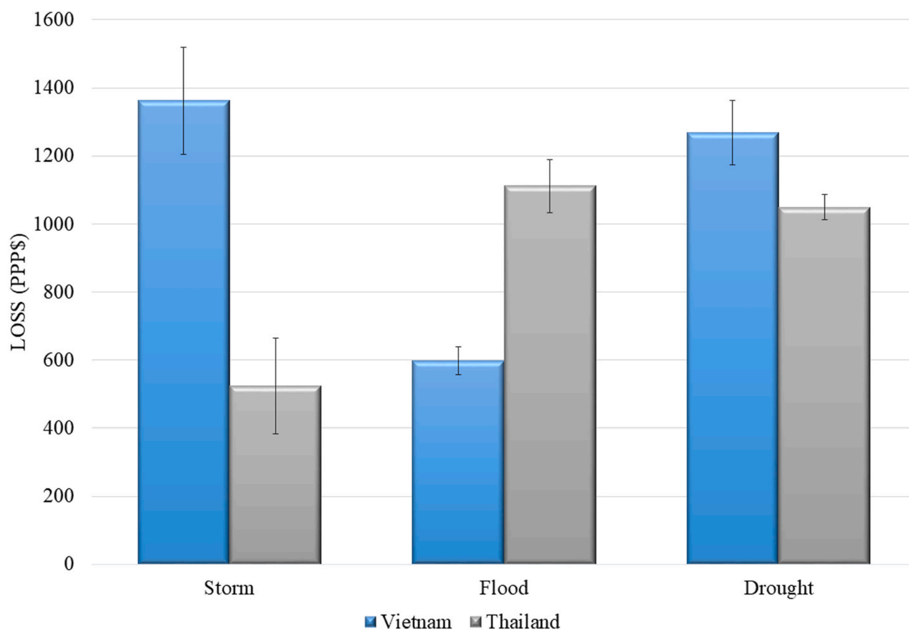

Fig. 4. Average loss due to weather shocks of an affected household (US$ PPP).

reduces the damage of floods (Hoddinott and Quisumbing, 2010).

Table 2 presents the key characteristics of the surveyed households in the study sites by year. In addition to weather shocks, household members in Central Vietnam are more exposed to health problems than in Northeast Thailand. Regarding farmland, the average farmland area per household is 4 times higher in Thailand, which is also in line with the finding of Praneetvatakul et al. (2013) that Thai households have larger farms than Vietnamese households. In terms of livestock holding, the monetary value of livestock per household does not differ significantly between the two countries but it has been increasing in both countries over time. Thai households borrow more than their Vietnamese fellows which is reasonable since more financial institutions are available in Thailand. The number of phones used by household members is shown to increase over time in both countries. This trend is also similar for the

Table 2
Descriptive statistics of main household and village characteristics by year and country.

	Vietnam				Thailand			
	2010	2013	2016	Δ(16–10)	2010	2013	2016	Δ(16–10)
sick	0.22	0.19	0.19	−0.03**	0.11	0.15	0.11	0.00
(number)	(0.45)	(0.45)	(0.43)	(0.01)	(0.32)	(0.36)	(0.31)	(0.01)
farmland	0.52	0.50	0.68	0.15***	2.18	1.67	1.37	−0.81***
(ha)	(0.74)	(1.59)	(1.28)	(0.03)	(2.61)	(2.89)	(1.61)	(0.07)
livestock	1.10	1.20	1.73	0.63***	1.08	1.19	1.95	0.87***
(1000 PPP$)	(1.87)	(2.03)	(2.89)	(0.08)	(1.84)	(2.81)	(4.17)	(0.1)
borrow	1.54	1.17	2.13	0.59***	1.79	1.84	2.07	0.28*
(1000 PPP$)	(5.74)	(4.06)	(5.95)	(0.19)	(4.28)	(5.54)	(5.52)	(0.16)
motorbike	0.98	1.26	1.52	0.53***	1.25	1.42	1.46	0.21***
(number)	(0.86)	(0.99)	(1.08)	(0.03)	(0.89)	(1.01)	(0.99)	(0.03)
tractor	0.33	0.38	0.21	−0.12***	0.52	0.54	0.51	−0.01
(number)	(0.51)	(0.58)	(0.45)	(0.02)	(0.6)	(0.63)	(0.63)	(0.02)
phone	1.41	2.12	2.53	1.12***	1.85	2.10	2.34	0.49***
(number)	(1.29)	(1.5)	(1.48)	(0.04)	(1.31)	(1.46)	(1.97)	(0.05)
family_size	4.21	3.97	3.78	−0.43***	4.01	3.91	3.66	−0.35***
(people)	(1.75)	(1.75)	(1.64)	(0.05)	(1.72)	(1.73)	(1.66)	(0.05)
labor_share	67.05	61.43	54.92	−12.13***	71.48	64.57	56.75	−14.73***
(%)	(26.01)	(26.19)	(26.39)	(0.84)	(21.83)	(24.83)	(27)	(0.78)
male_head	82.55	80.58	79.64	−2.91**	72.13	69.39	66.04	−6.09***
(%)	(37.96)	(39.57)	(40.28)	(1.26)	(44.85)	(46.10)	(47.37)	(1.46)
age_head	50.80	53.55	55.35	4.55***	57.36	59.40	61.27	3.91***
(years)	(13.62)	(13.35)	(12.59)	(0.42)	(12.73)	(12.46)	(11.83)	(0.39)
ethnic minority	20.23	21.08	20.79	0.57	0.06	0.06	0.06	0.00
(%)	(40.18)	(40.8)	(40.59)	(1.3)	(0.24)	(0.24)	(0.24)	(0.01)
farmers	83.74	86.50	86.87	3.13**	82.45	80.83	79.87	−2.58**
(%)	(36.91)	(34.18)	(33.78)	(1.14)	(6.20)	(6.12)	(6.03)	(0.18)
school_head	6.75	6.73	6.67	−0.08	4.93	4.89	5.23	0.30***
(years)	(4.01)	(3.99)	(3.98)	(0.13)	(2.92)	(2.97)	(3.05)	(0.09)
road_village	96.88	95.85	92.71	−4.16***	0.97	0.95	1.00	0.03***
(%)	(17.4)	(19.96)	(26)	(0.71)	(0.17)	(0.22)	(0)	(0)
internet_village	2.19	5.09	10.69	8.50***	2.27	3.55	4.46	2.19***
(%)	(7.87)	(8.12)	(15.2)	(0.38)	(5.79)	(10.59)	(8.38)	(0.23)

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$; standard deviations in parentheses, PPP US$ in 2005, Δ(16–10) is the change from 2010 to 2016.

number of motorbikes. However, the number of tractors per household is higher in Thailand than in Vietnam. The household size is not significantly different between these two countries and has been decreasing. However, Thailand has a higher share of female-headed households and each household in Thailand has a higher share of laborers. This is because the share of children in Vietnam is 1.2 times higher than that in Thailand, while the share of the elders is not significantly different between these two countries. The average education level of household heads is about 5 years in Thailand and 7 years in Vietnam, which is also in agreement with Klasen et al. (2015) that the heads of rural households in both countries have a low education level but in general, the education level of rural household heads in Vietnam is higher than in Thailand. With regard to the village characteristics, the share of households with access to internet is higher in Vietnam than in Thailand.

The differences in livelihood platforms presented above lead to the differences in the welfare of rural households (per capita income and consumption) between the two countries (Table 3). The common trend in the two countries is that these indicators have been increasing over time (Fig. 5). Farmers in Thailand are better off than their Vietnamese fellows. However, the growth in income and in consumption of Vietnamese households is higher than that of Thai households. This is reasonable because Vietnam has experienced rapid economic growth in recent decades. During the period from 2010 to 2016, the annual growth of GDP in Vietnam was higher than that in Thailand (7.5% vs. 3% (World Bank, 2017a,b)). Regarding sources of income, the growth in farm income is similar in the two countries. Meanwhile, non-farm income in Vietnam increases faster than in Thailand (57% vs. 43%, respectively). Regarding consumption, Vietnamese households have also experienced higher growth in food, non-food and total consumption. In both countries, the share of expenditure for food appears to decrease significantly. In 2010, the share of expenditure for food in Vietnam and Thailand was about 50%. This figure reduced to less than 40% in 2016.

4.2. Impact of weather shocks on household income

The results of the village-fixed effect regressions on the impacts of weather shocks and other factors on household income in Vietnam and Thailand are presented in Table 4. Regarding weather shocks, all types of weather shocks appear to significantly affect household income in Vietnam. Storms and droughts negatively affect per capita income and per capita non-farm income. Meanwhile, floods seem to negatively affect per capita farm income. In Thailand, floods and droughts negatively affect per capita income and per capita non-farm income. Droughts also decrease per capita farm income..These results are consistent with Figure 4, which shows that storms and droughts cause higher damages to households in Vietnam, whereas in Thailand floods and droughts have more severe income effects.

For other factors, health shocks have negative effects on per capita income, per capita farm income and per capita non-farm income in Vietnam. In terms of natural capital, the size of farmland and the value of livestock, which play an important role in households' agricultural production, are significantly and positively associated with per capita farm income in both countries. However, these variables are negatively associated with per capita non-farm income of Vietnamese households. This indicates that Vietnamese households with a larger farmland size or larger livestock holding specialize more in farming and participate less in non-farm activities. These results are consistent with Nguyen et al. (2017) who report that Vietnamese households with a larger farmland area tend to have less labor diversification. Regarding physical capital, the number of tractors is associated with a higher per capita farm income in both countries, indicating the important role of mechanization in agricultural production. In both countries, the number of motorbikes increases both per capita farm income and per capita non-farm income. In terms of social capital, the number of phones has a positive effect on non-farm income in both countries. This implies that households with better networking capacity may have more chances to work in non-farm sectors. Ethnic minority households are shown to have lower per capita non-farm income than ethnic majority households in Vietnam. This is reasonable as these households generally have lower education levels and most of them live in remote areas, therefore they could suffer more constraints in getting non-farm jobs (Nguyen et al., 2020c). Regarding human capital, households with a smaller family size and a higher number of laborers tend to have higher income in both countries. The gender of household head is also significantly associated with per capita farm income in both countries. In Thailand, male-headed households also tend to have higher non-farm income. Arouri et al. (2015) also report that female-headed households in Vietnam tend to have a significantly lower share of farm income than male-headed households. In terms of education, households with higher education level of the heads appear to have higher per capita income and per capita non-farm income in both countries. This result is reasonable because households being trained and educated are more likely to get well-paid jobs or they could take advantage of their knowledge to generate higher income than low-educated households (Nguyen et al., 2020c). At the village level, the internet accessibility has a significant and positive effect on per capita income and per capita nonfarm income in Vietnam.

4.3. Impact of weather shocks on household consumption

Table 5 presents the results of the village-fixed effects regressions on the effects of weather shocks and other factors on household consumption. Some of these factors are common to both countries, but other factors are specific to each country. Regarding weather shocks, the results reveal that their impact on household consumption is different

Table 3
Descriptive statistics of household welfare indicators by year and country (US$ 1000 PPP).

	Vietnam				Thailand			
	2010	2013	2016	Δ(16–10)	2010	2013	2016	Δ(16–10)
per capita *consumption (1000 PPP$)*	1.22	1.67	2.22	0.99***	1.80	2.21	2.84	1.03***
	(0.85)	(1.3)	(1.74)	(0.04)	(1.51)	(1.81)	(2.27)	(0.06)
per capita *food consumption (1000 PPP$)*	0.63	0.83	0.87	0.25***	0.82	0.97	0.89	0.07***
	(0.34)	(0.54)	(0.57)	(0.01)	(0.56)	(0.76)	(0.63)	(0.02)
per capita *non-food consumption (1000 PPP$)*	0.60	0.84	1.34	0.75***	0.98	1.24	1.94	0.96***
	(0.62)	(0.99)	(1.35)	(0.03)	(1.19)	(1.41)	(1.99)	(0.05)
per capita *income (1000 PPP$)*	1.67	2.01	2.83	1.16***	2.40	2.52	3.15	0.75***
	(2.1)	(2.57)	(3.12)	(0.08)	(2.89)	(3.61)	(3.7)	(0.11)
per capita *farm income (1000 PPP$)*	0.49	0.58	0.77	0.28***	0.49	0.62	0.71	0.21***
	(0.88)	(1.27)	(1.58)	(0.04)	(1.07)	(1.31)	(1.41)	(0.04)
per capita *non-farm income (1000 PPP$)*	1.03	1.24	1.70	0.67***	1.77	1.90	2.01	0.24
	(2.33)	(2.42)	(3.72)	(0.1)	(4.35)	(5.37)	(5.01)	(0.15)

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$; standard deviations in parentheses, PPP US$ in 2005, Δ(16–10) is the change from 2010 to 2016.

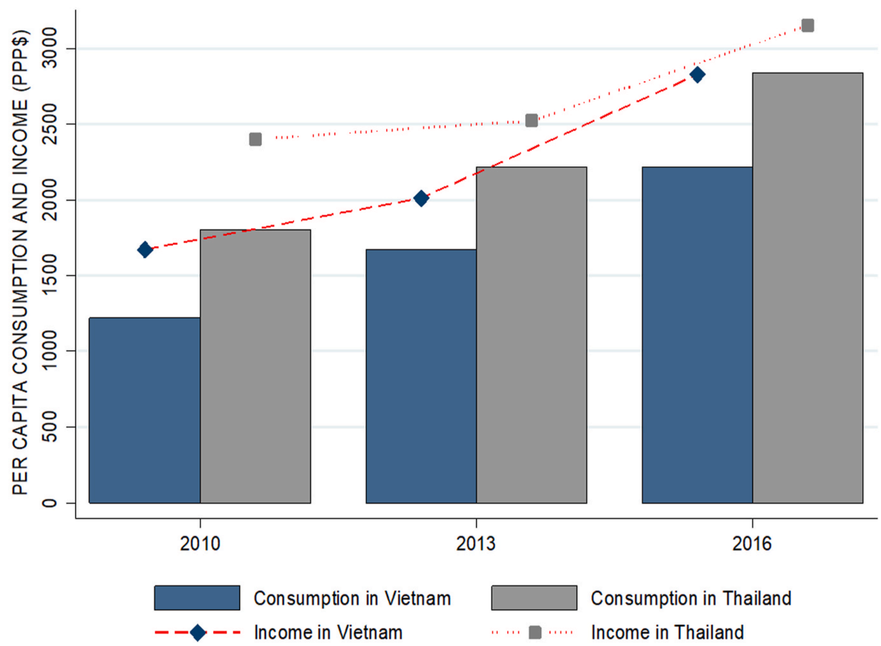

Fig. 5. Per capita income and consumption of surveyed households (US$ PPP).

between the two countries. In Vietnam, floods seem not to have a significant effect but storms and droughts have significant and negative effects on per capita consumption. In particular, storms negatively affect per capita consumption and per capita non-food consumption, meanwhile droughts decrease per capita consumption and per capita food consumption. The results are consistent with Bui et al. (2014). In Thailand, droughts are the most severe to household consumption. They negatively affect per capita consumption and per capita food consumption.

The sicknesses or deaths of household members decrease per capita food consumption but increase per capita non-food consumption in Vietnam. The increase in non-food consumption is mainly due to the increase in health expenditure for the household members who are sick. In Thailand the effects of the sicknesses are insignificant. This again confirms the argument that Thai farmers are able to smooth their consumption better than Vietnamese farmers. With regard to farm characteristics, the size of farmland is positively associated with per capita consumption and per capita food consumption in Vietnam and with per capita consumption, per capita food and non-food consumption in Thailand. This is reasonable as farmland size in Thailand is higher than in Vietnam. Therefore, it may allow Thai households to improve household consumption. In Vietnam, livestock is found to have positive effects on per capita consumption (also for food and non-food). The positive effect of livestock on household consumption in Vietnam is in line with Do et al. (2019) who report that livestock production plays an essential role in increasing household consumption in Vietnam. In terms of physical and social capital, the main productive asset (number of tractors) and the main transportation means (number of motorbikes) and the main communication means (number of phones) of rural households in both countries have positive effects. This also confirms the common notion that rural households, who are better off, are also more capable of coping with extreme weather events. The intuition of this finding is that, promoting mechanization and rural infrastructure and facilitating rural networking might be beneficial to rural households in mitigating the negative effects of weather shocks on household consumption. Our findings also show that ethnic minority households have lower per capita consumption, per capita food and non-food consumption than ethnic majority households. In both countries, the effects of family size and education of household heads are similar. An increase in the family size is associated with a decrease in per capita consumption, whereas an increase in education level of household heads is associated with an increase in per capita consumption. Male-headed households seem to be better-off in terms of per capita food consumption in both countries. In Vietnam, these households also have a higher level of total consumption. Regarding village characteristics, internet access shows positive effects on per capita consumption, per capita food and non-food consumption in Vietnam.

4.4. Impact of weather shocks on household poverty

Table 6 presents the results of the village-fixed effects regressions on the effects of weather shocks and other factors on income poverty and consumption poverty. Columns 1 and 3 are on consumption poverty, whereas columns 2 and 4 are on income poverty. Similar to the results of the regressions on household consumption and household income presented in the above subsections, the results in this subsection also show that some factors commonly affect poverty in both countries. However, some other factors are unique to each country. Regarding weather shocks, all extreme weather events considered in our study (storms, floods, and droughts) seem to have effects on either income poverty or consumption poverty. In Vietnam, the causes of income poverty include storms, floods, and droughts, whereas in Thailand these are floods and droughts.

For household characteristics, the effects of household size, motorbikes, phones, livestock, and education of household head on poverty are similar between the two countries. Households with more motorbikes, more phones, and better-educated household heads are less likely to all into consumption and income poverty. Livestock has a negative effect on both income poverty and consumption poverty in both countries. This is consistent with Do et al. (2019), who report that livestock production plays an important role in reducing both income and consumption poverty. Farmland size is negatively associated with consumption poverty in both countries. In addition, the increase in farmland size also reduces income poverty in Thailand. Farmland size is negatively associated with consumption poverty in both countries. In addition, the increase in farmland size also reduces income poverty in Thailand. In terms of human capital, the share of working-age members is negatively correlated with income poverty in Vietnam.

Table 4
Impact of weather shocks on rural household income (village fixed effects).

	Vietnam			Thailand		
	Per capita income	Per capita farm income	Per capita non-farm income	Per capita income	Per capita farm income	Per capita non-farm income
	(1)	(2)	(3)	(4)	(5)	(6)
storm	−240.717**	−25.387	−178.006**	−96.677	−127.850	−360.179
	(96.924)	(56.861)	(85.928)	(290.146)	(102.815)	(325.565)
flood	−62.512	−67.739*	−62.202	−411.085***	24.891	−460.594**
	(88.896)	(38.634)	(66.515)	(141.730)	(91.258)	(187.916)
drought	−122.947*	5.843	−304.003***	−465.410***	−194.498***	−452.832***
	(73.177)	(45.697)	(72.924)	(95.616)	(42.071)	(138.302)
sick	−136.762**	−45.536*	−164.152***	−152.076	−35.112	−174.129
	(60.962)	(26.347)	(57.464)	(118.072)	(46.208)	(171.492)
farmland (ln)	0.022	65.346***	−100.033***	112.877***	81.904***	37.538
	(20.962)	(10.906)	(26.137)	(19.987)	(6.671)	(27.456)
livestock (ln)	9.363	25.711***	−38.900***	19.297	34.489***	−36.654*
	(10.537)	(5.937)	(13.828)	(12.742)	(5.664)	(20.029)
motorbike	567.908***	115.227***	404.715***	421.866***	64.682***	512.841**
	(52.224)	(25.566)	(58.692)	(104.540)	(20.930)	(218.341)
tractor	275.911***	349.136***	−110.820	178.627	157.145***	102.680
	(94.101)	(59.270)	(89.282)	(112.916)	(42.730)	(189.130)
phone	222.285***	−8.077	209.584***	223.394***	24.994*	285.918***
	(42.113)	(18.910)	(55.943)	(74.041)	(13.212)	(93.632)
borrow (ln)	−0.937	−6.551*	5.766	2.437	0.523	11.017
	(8.266)	(3.831)	(8.962)	(12.479)	(3.976)	(19.149)
family_size	−388.140***	−31.357***	−6.456	−424.677***	−51.835***	−18.021
	(28.204)	(11.057)	(23.220)	(46.857)	(12.398)	(57.378)
labor_share	2.176	−0.148	3.614**	9.953***	2.473***	11.017***
	(1.515)	(0.815)	(1.395)	(2.402)	(0.706)	(3.613)
male_head	−15.220	106.672***	−1.641	104.802	68.339*	323.040**
	(110.842)	(34.559)	(97.121)	(101.569)	(35.545)	(138.463)
age_head	−1.628	−2.106	−25.840***	7.308	−0.264	−13.076*
	(2.913)	(1.448)	(3.982)	(5.701)	(1.541)	(7.897)
ethnic minority	−95.611	−129.845	−894.377***	−111.517	−45.349	−180.054
	(284.753)	(245.543)	(287.648)	(187.506)	(80.599)	(237.156)
farmer	−473.236***	33.990	−684.707***	−617.012***	48.286	−1126.634***
	(131.922)	(53.778)	(177.101)	(192.570)	(42.545)	(277.539)
school_head	56.871***	7.322	35.158**	195.657***	10.087	214.242***
	(13.040)	(5.500)	(13.861)	(29.964)	(6.794)	(36.764)
road_village	−157.453	120.261	−130.863	410.736	68.409	288.592
	(168.619)	(88.694)	(154.580)	(296.460)	(117.051)	(343.565)
internet_village	20.940***	3.174	17.385***	−0.839	−3.094	1.100
	(5.126)	(3.714)	(4.579)	(5.845)	(2.371)	(7.531)
2010	−300.465***	−244.624***	−195.131	−518.751***	−289.640***	−110.747
	(107.953)	(58.138)	(124.252)	(125.443)	(40.727)	(192.443)
2013	−459.850***	−197.455***	−243.198***	−410.560***	−71.690*	−29.030
	(95.547)	(51.969)	(90.655)	(118.174)	(42.321)	(174.051)
constant	2846.94***	686.634***	2126.128***	1872.572***	665.842***	172.260
	(384.867)	(191.791)	(420.743)	(666.244)	(179.442)	(904.370)
Observations	5809	5809	5809	5833	5833	5833
R^2 overall	0.173	0.088	0.108	0.122	0.112	0.072
Prob. > F	0.000	0.000	0.000	0.000	0.000	0.000

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$; standard errors clustered at village level in parentheses.

Female-headed households are more likely to be income poor in Thailand. With regard to financial and physical capital, the amount of loans and number of tractors are negatively associated with consumption poverty in both countries.

5. Conclusion

Rural households in developing countries are exposed and vulnerable to weather shocks. Assessing welfare impacts of weather shocks on rural households and comparing the effects between countries provide useful information for establishing mitigation measures. This study employs the sustainable livelihoods framework to examine and compare the effects of storms, floods, and droughts, the most popular extreme weather events reported by rural households in Thailand and Vietnam on household income, consumption, and poverty. The village fixed effects regressions are used for a dataset of 5809 observations in three provinces of Central Vietnam and of 5833 observations in three provinces of Northeast Thailand. This allows for a comparative analysis of the effects since the same questionnaires and data collection methods were used during the same time periods of 2010, 2013, and 2016.

Our results show that rural households in Northeast Thailand and Central Vietnam are affected by storms, floods, and droughts in terms of income, consumption, and poverty although the severity is different in each country for each type of weather shock. Drought is the common extreme weather event in these two countries with significant and negative effects on household income, consumption, and poverty. Compared to Thailand, Vietnam is more exposed and significantly affected by storms due to its geographical position with a long coastline. Meanwhile, floods have higher effects on rural households in terms of income and poverty than storms do in Thailand. In addition to weather shocks, the welfare of rural households in these two countries is significantly affected by other factors representing the livelihood platforms of the households. The numbers of tractors and motorbikes and the education level of household heads are positively correlated with household income and consumption in both countries. Moreover, a larger farmland size would increase farm income and food consumption,

Table 5
Impact of weather shocks on household consumption (village fixed effects).

	Vietnam			Thailand		
	Per capita consumption (ln)	Per capita food consumption (ln)	Per capita non-food consumption (ln)	Per capita consumption (ln)	Per capita food consumption (ln)	Per capita non-food consumption (ln)
	(1)	(2)	(3)	(4)	(5)	(6)
storm	−0.035*	−0.018	−0.068**	−0.059	−0.046	−0.024
	(0.020)	(0.023)	(0.028)	(0.057)	(0.055)	(0.072)
flood	−0.013	−0.009	−0.018	−0.016	0.038	−0.063
	(0.023)	(0.023)	(0.031)	(0.029)	(0.027)	(0.039)
drought	−0.033**	−0.037*	−0.023	−0.027*	−0.041**	−0.005
	(0.015)	(0.020)	(0.021)	(0.016)	(0.016)	(0.021)
sick	0.016	−0.032**	0.061***	−0.006	−0.030	0.008
	(0.014)	(0.014)	(0.019)	(0.019)	(0.021)	(0.024)
farmland (ln)	0.008**	0.009**	0.009	0.031***	0.027***	0.033***
	(0.004)	(0.004)	(0.005)	(0.003)	(0.003)	(0.004)
livestock (ln)	0.008***	0.010***	0.008***	−0.000	0.002	−0.001
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
motorbike	0.197***	0.127***	0.274***	0.125***	0.048***	0.189***
	(0.009)	(0.009)	(0.013)	(0.012)	(0.009)	(0.018)
tractor	0.042***	0.014	0.074***	0.092***	0.072***	0.096***
	(0.014)	(0.016)	(0.018)	(0.015)	(0.014)	(0.019)
phone	0.091***	0.063***	0.119***	0.078***	0.035***	0.112***
	(0.006)	(0.006)	(0.008)	(0.023)	(0.011)	(0.032)
borrow (ln)	0.006***	0.002	0.009***	0.008***	0.006***	0.009***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
family_size	−0.169***	−0.151***	−0.181***	−0.185***	−0.178***	−0.183***
	(0.005)	(0.005)	(0.007)	(0.008)	(0.006)	(0.011)
labor_share	0.000	−0.000	0.001**	0.001***	0.000	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
male_head	0.052***	0.085***	0.018	0.011	0.042**	−0.013
	(0.019)	(0.019)	(0.026)	(0.019)	(0.018)	(0.024)
age_head	−0.001	−0.001	−0.002**	−0.000	−0.000	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ethnic minority	−0.173***	−0.096*	−0.271***	0.016	0.043	−0.002
	(0.045)	(0.054)	(0.050)	(0.042)	(0.039)	(0.055)
farmer	−0.056**	−0.030	−0.079**	−0.092***	−0.016	−0.139***
	(0.026)	(0.028)	(0.033)	(0.029)	(0.027)	(0.036)
school_head	0.023***	0.017***	0.029***	0.036***	0.016***	0.049***
	(0.002)	(0.002)	(0.003)	(0.004)	(0.003)	(0.005)
road_village	−0.042	−0.013	−0.077*	−0.012	0.007	−0.024
	(0.038)	(0.043)	(0.042)	(0.041)	(0.042)	(0.060)
internet_village	0.003***	0.002**	0.002***	0.001	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
2010	−0.257***	−0.056**	−0.447***	−0.330***	−0.028	−0.543***
	(0.021)	(0.022)	(0.026)	(0.020)	(0.019)	(0.026)
2013	−0.120***	0.069***	−0.327***	−0.160***	0.108***	−0.356***
	(0.018)	(0.022)	(0.020)	(0.016)	(0.018)	(0.021)
constant	7.571***	6.771***	6.897***	7.882***	7.043***	7.208***
	(0.074)	(0.077)	(0.095)	(0.081)	(0.080)	(0.108)
Observations	5809	5809	5809	5833	5833	5833
R^2 overall	0.486	0.309	0.492	0.389	0.250	0.391
Prob. > F	0.000	0.000	0.000	0.000	0.000	0.000

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$; standard errors clustered at village level in parentheses.

and decrease consumption poverty in both countries. A larger livestock holding would increase household consumption in Vietnam. In addition, the development of internet access are shown to significantly and positively affect household income and consumption in Vietnam. Ethnic minority households in Vietnam appear to have lower per capita non-farm income and per capita consumption than ethnic majority households.

These findings lead to several important implications. Promoting farm mechanization and rural education should be given a high priority in both countries. In Thailand, the accumulation of farmland should also be encouraged. In Vietnam, supporting livestock production would contribute to increasing household consumption and reducing poverty. In addition, investing more in internet infrastructure should be given a high priority as it contributes to increasing income and consumption of households in Vietnam.

Even though our study provides useful insights on the welfare effects of extreme weather events in the two countries, it still has a number of limitations. First, the data on extreme weather events are reported by rural households. On the one hand, this reflects the effects observed by the households. On the other hand, the data might suffer from reporting biases. Therefore, future studies should consider using measured weather data to validate the reported extreme weather events. Second, our fixed effects regressions are not able to account for time variant factors. For a longer panel, this might be an important issue that needs to be addressed with other econometric models.

CRediT authorship contribution statement

Trung Thanh Nguyen: Conceptualization, data processing and writing. **Thanh-Tung Nguyen:** Data processing and reviewing. **Van-Hanh Le:** Data processing. **Shunsuke Managi:** Conceptualization and editing. **Ulrike Grote:** Conceptualization and editing.

Declaration of competing interest

The authors declare that they have no known competing financial

Table 6
Impact of weather shocks on poverty ($US 1.9 PPP) (village fixed effects).

	Vietnam		Thailand	
	Consumption Poverty	Income Poverty	Consumption Poverty	Income Poverty
	(1)	(2)	(3)	(4)
storm	*0.031*	*0.055***	*0.007*	*0.066*
	(0.021)	*(0.024)*	*(0.024)*	*(0.048)*
flood	*0.015*	*0.052***	*−0.003*	*0.045***
	(0.022)	*(0.024)*	*(0.013)*	*(0.022)*
drought	*0.014*	*0.025**	*0.002*	*0.037****
	(0.012)	*(0.015)*	*(0.006)*	*(0.013)*
sick	*−0.000*	*0.018*	*0.004*	*0.028**
	(0.010)	*(0.013)*	*(0.009)*	*(0.015)*
farmland (ln)	*−0.005***	*−0.002*	*−0.006****	*−0.010****
	(0.003)	*(0.003)*	*(0.001)*	*(0.002)*
livestock (ln)	*−0.008****	*−0.007****	*−0.001**	*−0.004****
	(0.001)	*(0.002)*	*(0.001)*	*(0.001)*
motorbike	*−0.051****	*−0.071****	*−0.026****	*−0.033****
	(0.006)	*(0.008)*	*(0.004)*	*(0.006)*
tractor	*−0.027****	*−0.017*	*−0.016****	*−0.018**
	(0.009)	*(0.011)*	*(0.004)*	*(0.010)*
p>hone	*−0.035****	*−0.034****	*−0.013****	*−0.018****
	(0.004)	*(0.005)*	*(0.003)*	*(0.005)*
borrow (ln)	*−0.003****	*−0.001*	*−0.003****	*−0.004****
	(0.001)	*(0.001)*	*(0.001)*	*(0.001)*
family_size	*0.053****	*0.040****	*0.031****	*0.033****
	(0.004)	*(0.004)*	*(0.003)*	*(0.005)*
labor_share	*−0.000*	*−0.001****	*0.000*	*−0.000*
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*
male_head	*−0.005*	*−0.018*	*−0.012*	*−0.024***
	(0.015)	*(0.016)*	*(0.008)*	*(0.012)*
age_head	*0.000*	*−0.000*	*0.001**	*−0.000*
	(0.000)	*(0.001)*	*(0.000)*	*(0.001)*
ethnic minority	*0.102****	*0.076***	*0.004*	*0.014*
	(0.038)	*(0.035)*	*(0.018)*	*(0.027)*
farmer	*0.010*	*0.052***	*−0.007*	*0.031**
	(0.016)	*(0.021)*	*(0.010)*	*(0.016)*
school_head	*−0.009****	*−0.007****	*−0.003****	*−0.004***
	(0.002)	*(0.002)*	*(0.001)*	*(0.002)*
road_village	*0.023*	*−0.046*	*0.009*	*−0.050*
	(0.023)	*(0.030)*	*(0.020)*	*(0.033)*
internet_village	*0.000*	*−0.001*	*0.000*	*0.001*
	(0.000)	*(0.001)*	*(0.001)*	*(0.001)*
2010	*0.066****	*0.062****	*0.059****	*0.064****
	(0.013)	*(0.017)*	*(0.008)*	*(0.013)*
2013	*−0.002*	*0.101****	*0.012***	*0.105****
	(0.011)	*(0.015)*	*(0.006)*	*(0.013)*
constant	*0.024*	*0.279****	*−0.062**	*0.112**
	(0.050)	*(0.059)*	*(0.034)*	*(0.064)*
Observations	5809	5809	5833	5833
R^2 overall	0.168	0.127	0.094	0.066
Prob. > F	0.000	0.000	0.000	0.000

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$; standard errors clustered at village level in parentheses.

interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.wace.2020.100286.

Annex 1
Hausman tests for the fixed effects vs. random effects regression models

Model	Chi^2 (19)	Prob.>chi^2
per capita consumption (Vietnam) (ln)	133.93	0.000
per capita food consumption (Vietnam) (ln)	127.38	0.000
per capita non-food consumption (Vietnam) (ln)	124.68	0.000
per capital income (Vietnam)	41.64	0.005
per capital farm income (Vietnam)	114.31	0.000
per capital non-farm income (Vietnam)	31.40	0.067

(*continued on next page*)

Annex 1 (*continued*)

Model	Chi^2 (19)	Prob.>chi^2
consumption poverty (Vietnam)	117.36	0.000
income poverty (Vietnam)	50.62	0.000
per capita consumption (Thailand) (ln)	100.14	0.000
per capita food consumption (Thailand) (ln)	52.65	0.000
per capita non-food consumption (Thailand) (ln)	100.41	0.000
per capital income (Thailand)	21.78	0.412
per capital farm income (Thailand)	52.22	0.000
per capital non-farm income (Thailand)	18.57	0.612
consumption poverty (Thailand)	50.68	0.000
income poverty (Thailand)	30.82	0.076

Annex 2
Multicollinearity test (Variance Inflation Factor Test)

Variable	Variance Inflation Factor (VIF)	
	Vietnam	Thailand
storm	1.13	1.01
flood	1.05	1.02
drought	1.09	1.07
sick	1.02	1.02
farmland (ln)	1.88	1.86
livestock (ln)	1.27	1.19
motorbike	1.92	1.40
tractor	1.17	1.27
phone	2.01	1.34
borrow (ln)	1.11	1.11
family_size	1.39	1.311
labor_share	1.40	1.38
male_head	1.17	1.09
age_head	1.34	1.43
ethnic minority	1.39	1.01
farmer	1.78	1.87
school_head	1.33	1.24
road_village	1.03	1.03
internet_village	1.21	1.06
2010	1.56	1.44
2013	2.09	1.60
Mean	**1.40**	**1.27**

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