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Natural Disasters and Household Welfare

Evidence from Vietnam

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Abstract

As natural disasters hit with increasing frequency, especially in coastal areas, it is imperative to better understand how much natural disasters affect economies and their people. This requires disaggregated measures of natural disasters that can be reliably linked to households, the first challenge this paper tackles. In particular, a methodology is illustrated to create natural disaster and hazard maps from first hand, geo-referenced meteorological data. In a second step, the repeated cross-sectional national living standard measurement surveys (2002, 2004, and 2006) from Vietnam are augmented with the natural disaster measures derived in the first phase, to estimate the welfare effects associated with natural disasters. The results indicate that short-run losses from natural disasters can be substantial, with riverine floods causing welfare losses of up to 23 percent and hurricanes reducing welfare by up to 52 percent inside cities with a population over 500,000. Households are better able to cope with the short-run effects of droughts, largely due to irrigation. There are also important long-run negative effects, in Vietnam mostly so for droughts, flash floods, and hurricanes. Geographical differentiation in the welfare effects across space and disaster appears partly linked to the functioning of the disaster relief system, which has so far largely eluded households in areas regularly affected by hurricane force winds.

This paper—a product of the Poverty and Inequality Team, Development Research Group—is part of a larger effort in the department to understand household vulnerability to weather-related shocks. Policy Research Working Papers are also posted on the Web at http://econ.worldbank.org. The author may be contacted at pflewitt@worldbank.org.

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1 Natural Disasters and Welfare

As the world prepares for a changing climate and natural disasters hit with increasing frequency (UNISDR, 2009), especially in coastal areas (Costanza and Farley, 2007), it is imperative to better understand how natural disasters affect economies and their people. While disasters are known to cause substantial human and economic suffering (Okuyama, 2009), there remain important uncertainties about the magnitudes of the welfare loss and its persistence over time, the heterogeneity in their effects across socio-economic groups, the conditions under which they are more or less harmful, and the effectiveness of different interventions in dealing with them. When it comes to economic or GDP growth (as opposed to welfare/GDP levels), there isn't even an empirical or theoretical consensus about whether natural disasters are actually damaging for growth (not levels) or not (Cavallo and Noy, 2009; Loyaza, et al., 2009).

Careful examination of the welfare effects of natural disasters requires in the first place a disaggregated mapping of the natural disasters themselves. While the (economics) literature typically glances over this, this is anything but straightforward. For example, micro-studies nowadays often use subjective measures of shocks and disasters.[2] When available, these are useful, but also suffer from important methodological and practical shortcomings. In particular, whether a household considers a meteorological event a natural disaster is likely to depend both on its ex ante exposure to it and its ex post capacity to cope with it. Yet, to reduce its exposure it may have adopted less risky portfolio strategies over time, which could come at the expense of lower average returns. The household may also be able to fall back on (formal or informal) support systems to cope with it ex post, leading it to consider the event less of a shock or disaster, as it is not bearing its full costs. Such considerations, which remain largely unknown to the researcher, may lead to an underestimation of the full welfare cost of the event. Besides methodological concerns, it is typically also hard to extrapolate the findings across space and time, as subjective shock measures are usually not available outside the sample. Neither are their probability distributions, which are necessary to predict in the future.[3] When objective measures of natural disasters have been used instead, for example directly derived from the weather data, these measures have often been constructed only at rather aggregated levels (Christiaensen and Subbarao, 2005).

To overcome these methodological and practical concerns, this study derives measures of natural disasters and hazards at disaggregated geographical levels from primary meteorological weather station data, storm tracks and satellite observations. Second, in understanding the economic impact from disasters both direct and indirect effects need to be considered. Their most direct (and visible) impact relates to the destruction of capital (for example productive assets, property and infrastructure in case of floods and hurricanes; livestock and crop loss, but also hunger and reduced work capacity in case of droughts and famines) (Loyaza, et al., 2009). But they also have important indirect effects (Okuyama, 2009), as the effects of the initial destruction of private and public capital works its way through the economy via the product and factor markets. Ruptures in infrastructure or the electricity supply for example reduce the flow of goods and services and

[2] These are typically derived from answers to a shock module incorporated in household questionnaires asking respondents whether they experienced different types of shocks over a certain period (e.g. a drought, a flood, a storm, …).
[3] The latter could in theory be obtained (Delavande, Gine and McKenzie, 2010).

interrupt manufacturing processes thereby diminishing the returns to capital. Droughts cause food prices to rise and livestock prices to tumble (the latter in the face of collapsing demand for meat, Barrett (2001)). The effects of disasters may also be felt in the labor markets, with wages often substantially lower several years after the event (Jayachandran, 2006; Mueller and Osgood, 2009). Quisumbing and Mueller (2010) estimated for example that for each one foot deviation from the normal flood level agricultural and non-agricultural wages were 4 to 7 percent lower five years after the 1998 flood of the century in Bangladesh.

Whether and the extent to which a household also sees its income and consumption reduced, depends further on its exposure to the disaster and its capacity to cope with it ex post (Dercon, 2002; Hasegawa, 2010). Those with irrigated fields or those earning their living outside agriculture are for example less likely to suffer from droughts, while domestic and foreign remittances and well targeted disaster relief can make up for a substantial part of the income loss. The better credit and insurance markets work, the better households are usually also able to cope with disasters and the less they see their consumption decline (Lopez, 2009). Furthermore, in the aftermath of the disaster, there may also be a temporary boost in certain sectors such as construction (building-back) opening up opportunities for certain groups. The Keynesian type construction boom may even accelerate the overall growth rate if it results in an accelerated upgrading of the existing capital stock (building-back-better; Hallegatte and Dumas, 2009).

To capture both direct and indirect effects and illuminate the implicit costs associated with some of the coping strategies, this study pursues a fully reduced form analysis at the household level (very much in the spirit of Dercon, 2004). In particular, it examines the effect of natural disasters on household consumption, using disaggregated (objective) disaster measures derived from geo-referenced meteorological data and controlling for some of the coping strategies. The overall objective of the study is thus twofold: 1) to develop and illustrate a methodology to construct more objective and disaggregated natural hazard and disaster maps from primary meteorological data; and 2) to illustrate a methodology to estimate the expected welfare loss associated with natural disasters based on such natural hazard and disaster maps.

By deriving natural disaster measures from historical weather data several of the methodological and practical challenges associated with subjective measures can be mitigated. Furthermore, though not pursued in this study, the hazard and disaster maps thus obtained can also be used for planning and targeting purposes. In estimating the welfare loss, an estimator which simultaneously accounts for heteroskedasticity, survey design (cluster effects), and spatial correlation is also developed. Though oft ignored, as the effects of natural disasters permeate through the economy, spatial correlation in consumption following a disasters is likely. Ignoring this may cause bias and reduce the efficiency of the estimation procedures. To be clear, an in depth examination of the channels through which the different disasters affect welfare is not aspired. Nonetheless, a limited exploration of the effects of disasters on intermediary outcomes is presented to facilitate an intuitive interpretation of the reduced form findings. Potential persistence of the effects and heterogeneity across key socio-economic groups is also explored.

The empirical application is to Vietnam, which UNISDR (2009) ranked fourth in the world in terms of the absolute number of people exposed to floods; tenth in terms of the absolute number of people exposed to high winds from tropical cyclones, and sixteenth in terms of the absolute number of people exposed to drought. The regular occurrence of natural disasters together with the availability of three highly comparable nationally representative household living standard surveys (2002-2004-2006) render Vietnam particularly suitable to illustrate the approach advanced in this paper. The study constructs in particular disaggregated maps of the annual occurrence of droughts, (local and riverine) floods and storms during 2001-2006 as well as the likelihood of their occurrence using meteorological data from rainfall stations, storm tracks, and satellite images. The occurrence of these geo-referenced disasters, further augmented with the likelihood of their occurrence derived from the historical weather records, is subsequently linked with household consumption and other household and location characteristics from the repeated nationally representative household surveys and secondary data sources to estimate the effect of extreme weather events on household welfare.

The results suggest that the immediate losses from floods and hurricanes can be substantial, with hurricanes causing most havoc (up to 52 percent consumption loss among households close to large urban centers). Households tend to cope well with droughts, largely through irrigation. Frequent exposure to disasters erodes the standard of living, but reduces the immediate effects of shocks as households become less exposed and better prepared. Households in frequently inundated areas have even been able to turn the floods into an advantage, as long as the flooding is not too severe. There is however no adaptation to hurricanes, rather the contrary, with high frequency of hurricanes exacerbating the losses from particular events. Finally, those further away from the large urban centers are not only poorer, but also tend to suffer less from disasters, likely due to the adoption of less risky (but less remunerative) portfolios and a higher likelihood of receiving disaster relief.

The next section outlines the approach used to obtain geographically disaggregated estimates of droughts, heavy rainfall, river floods and storms with hurricane force. Section three reviews the empirical methodology to estimate the welfare effects. Section four reviews the data used and section five presents the empirical findings regarding the welfare effects of different natural disasters. Section six concludes.

2 Mapping Natural Hazards

Vietnam's 2007 "National Strategy for Natural Disaster Prevention, Response and Mitigation to 2020" identifies droughts, floods, and cyclones as its most important natural hazards. Landslides, which often happen following flash floods or cyclones, are mentioned as well. One common approach to determine whether a household has been affected by an extreme weather event is to ask the household directly. In contrast to external measures of extreme weather events derived from spatially scattered weather stations or satellite data, self-reported shock measures have the advantage of being locally more accurate—households know whether they experienced an extreme weather event or not. They also circumvent the challenge of identifying the cut-off beyond which a particular meteorological variable or combination of meteorological variables constitutes an extreme weather event. Indeed, deciding when rainfall is too much or too little, when winds are too strong, flood levels too high, or temperatures too high or too low across a series of settings and groups is demanding.

Yet not only are subjectively reported shock modules often not included in standard household surveys, they also raise issues of endogeneity, especially when incorporated in consumption regressions. These can typically only be overcome through the use of panel data, which are rarely available at the national level. The location, time, and household specificity of the subjective shock data also limits generalizations across time and space. In contrast, knowledge of the historical distribution of weather patterns allows the construction of probability distributions of weather events, which is useful to explore patterns of adaptation over time. It also helps in controlling for potential endogeneity of the extreme weather event measures in the absence of panel data. Interpolation of the extreme weather event data across space further permits the construction of disaggregated natural hazard maps, a useful tool in the spatial allocation of interventions and the simulation of the welfare effects of changing climate patterns.

Several global meteorological databases are available. But with the exception of the cyclone databases (UNEP/GRID-Europe, 2007a,b) they do not have a high resolution typically. This paper exploits access to Vietnam's detailed historical daily weather station data from 166 stations across the country to generate geographically disaggregated rainfall maps at the 0.1-degree resolution (corresponding nominally to 11 km at the equator).[4] These data form the basis to derive geo-referenced local measures of drought and localized floods/heavy rainfall. To also capture riverine floods, which may occur downstream following heavy rainfall in the mountains or as a result of storm surges in coastal areas, riverine flood indicators will be constructed based on the satellite based flood data from the Dartmouth Flood Observatory (DFO) (2008). The 1980-2006 geo-referenced UNEP/GRID-Europe storm track dataset is used to separately explore the effects from high winds and gusts from cyclones. As the damage from heavy rainfall associated with cyclones will already be captured by the localized and riverine flood indicators, these measures will capture the wind damage associated with cyclones.[5]

Rainfall maps

To construct spatially disaggregated indicators of drought and excess rainfall, the weather station data must first be spatially interpolated and cut-offs must be determined beyond which precipitation is considered too little or too much. Spatial interpolation of weather data is a discipline in itself which has developed an array of techniques that go from the most crude and obvious (such as the nearest neighbor techniques[6]) to the more precise and resource intensive (such as the radial basis functions).[7] Nonetheless, as the complexity of the techniques increases, they also display rapidly decreasing returns in terms of precision given resources spent.[8] As the focus of the paper is

[4] The frequently used CRU TS2.1 monthly rainfall database (Mitchell and Jones, 2005) only has a half degree resolution, which is around 55 kilometres at the equator.
[5] See Thomas (2009) for a detailed description of the different data sources and a more elaborate description of the construction of the different natural hazard maps.
[6] The nearest neighbour method assigns the value of the weather station nearest to the grid cell centre.
[7] Radial basis functions are functions of distance used for exact interpolation of point data. They attempt to overlay a smooth surface on the point data, allowing for various degrees of bending in that surface through a smoothing parameter that is specified by the researcher. Common radial basis functions are thin-plate spline and multiquadratic functions. See De Smith et al. (2007) for a comprehensive textbook that is reasonably accessible.
[8] In a comparison of the performance of different interpolation techniques on rainfall data from May 8 1986 in Switzerland, the latter was found to be the most precise (Dubois, 2003). Yet, as highlighted by Dubois and Shilbi (2003), at 5.93 mm, the root mean square error (RMSE) for the multiquadratic function was only slightly

not on constructing highly accurate rainfall maps as such, necessary for example for the design of weather index insurance programs, but rather on the household welfare effects of weather related events, a pragmatic approach has been pursued here, aimed at minimizing measurement error of the disaggregated rainfall measures at a reasonable cost, while maintaining maximum replicability of the approach in other settings.

In particular, using the historical daily rainfall records over 1980-2006 in 166 geo-referenced weather stations from across Vietnam (see Figure 1)[9], monthly rainfall grids of 0.1 degree resolution are constructed[10] using both inverse distance weighting (IDW) and inverse elevation difference weighting (IEW). In IDW, one of the most widely used spatial interpolation techniques in practice (Tomczak, 2003), the rainfall value in a particular grid cell is obtained as the weighted average of the rainfall data from a predetermined set of neighboring weather stations (e.g. the 5 closest or all the neighboring stations within a certain distance) using the inverse distance between the station and the center of the grid cell (raised to a power) as weight and normalized by the sum of the weights.[11] The squared inverse distance to the five nearest stations for which data were available was chosen in the empirical application below. IDW exploits the intuition that the further away the station is, the less its rainfall pattern will resemble this at the point of interest. However, even over short distances rainfall patterns can still diverge widely, especially among locations at different altitudes (Hutchinson, 2003). Given its mountainous range, high slope gradients are frequently observed in Vietnam, with some grids displaying within grid elevation differences of more than 1,000 meters. To exploit this largely neglected insight (Dubois and Shilbi, 2003), an elevation difference weighted rainfall index based on the ten nearest stations is also constructed.[12]

The relative importance of both the IDW and IEW indices in determining rainfall in a grid is subsequently estimated through an ordinary least square regression of the log of the observed monthly rainfall patterns in the 166 stations during 1980-2006 on the log of their IDW and the log of their IEW index, monthly dummies and their interactions to allow for monthly variations in the

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better than this for IDW (6.3 mm), which is negligible compared to the average rainfall of 18.51 mm among the 367 omitted data points for which rainfall was interpolated from the remaining 100 rainfall stations.

[9] The average distance between rainfall stations is 32 km.

[10] While the satellite based rainfall maps produced by CPC/NOAA could also be used in principle, they only dated back to 2001, preventing us from constructing disaggregated historical rainfall patterns, necessary to explore patterns of adaptation. There is an additional concern as the satellite based CPC / NOAA data for Vietnam appear calibrated on a rather small number of rainfall stations (10 or so) from within Vietnam.

[11] To be precise, $IDW = r(x) = \sum_{k=0}^{N} \frac{w_k(x)}{\sum_k^N w_k(x)} r_k$ with r(x) the inverse distance weighted rainfall at interpolated point x, based on observed rainfall values r_k at k=0,1, …, N known interpolating (known) points x_k, with $w_k(x) = \frac{1}{d(x,x_k)^p}$ as weight, x_k an interpolating (known) point, d a given (Euclidean) distance from the known point x_k to the unknown point x and p a positive real number, the power parameter.

[12] Further corrections for anisotropy can be taken. This is important if nearness in one direction is more important than nearness in the perpendicular direction in determining the distance weights. This may be the case when mountain ranges are oriented at particular angles, or when prevailing winds are from a specific direction. This has not been pursued here, given the inclusion of the elevation difference in our final predictions and the reasonable prediction precision obtained when using both inverse distance squared and inverse elevation weighted indicators (see below).

relative importance of both indices.[13] The regression explained 76.8 percent of the observed variation in the monthly rainfall records from these stations (R-squared = 0.768), which provides some confidence in the predictive power of the method.[14] The IEW index carries substantially more weight in predicting rainfall during the wetter months (April-November), while the IDW index is also important in predicting rainfall during the dry months (December-March). An estimate of monthly rainfall for each grid cell was obtained by applying the estimated coefficients in Table A1 to their respective IEW and IDW indices. By way of illustration, Figure 1 presents the interpolated rainfall map for June 2006, both based on the regression prediction method and the IDW and IEW indices separately.

Drought maps

While Vietnam does receive large amounts of rainfall on average, moderate and severe droughts occur across the country, albeit with diverging frequency. They are more common and more severe in the Northeastern part of the country and the Red River Delta, but have also been reported in the Mekong Delta in the South, despite widespread irrigation.[15] In keeping with the study's focus on exogenous measures of a natural hazard, the focus here is on meteorological drought, defined as rainfall deficits over extended periods of time.[16] Unlike agricultural drought indices, meteorological ones also allow exploration of the (indirect) effects of droughts on urban households for example through water shortages and electricity outages.

A multitude of meteorological drought indices has been proposed in the literature (see Keyantash and Dracup (2002) for a review). Following Dilley et al (2005), the authors of the World Bank study "*Natural Disaster Hotspots: A Global Risk Analysis*", the cumulative precipitation anomaly index is taken. This is the deviation in precipitation from a long-term mean or median for a specific period of time, usually expressed as the proportion of the long term mean or median. It is straightforward to calculate and does not require other meteorological input (such as temperature data) and thus also no additional spatial interpolation. It is also flexible. It does not impose a distributional structure on the rainfall data, like the widely used Standardized Precipitation Index (SPI) (McKee et al., 1993). Furthermore, unlike the rainfall decile index, which ranks the historically observed rainfall in each location and considers rainfall episodes in the lowest decile(s) as droughts, the cumulative precipitation anomaly index also allows the likelihood of a drought in a particular area to vary across space. The latter is important to explore potential adaptation to frequent drought exposure, as will be seen later on.

[13] By taking log transformations, negative predictions are avoided and estimation issues related to the skewness of the rainfall data are mitigated.

[14] A similar degree of precision was registered in a series of modified specifications. Using a polynomial regression of the IEW and IDW indices reduces the root mean square error by 0.01 (from 0.764 in the current specification). Similarly, application of the interpolation on the log or squared root transformed values reduces the RMSE only by 0.03. Inclusion of time varying month dummies yields virtually no improvement, while inclusion of regional dummies reduces the RMSE by 0.05.

[15] The administrative regions of Vietnam are presented in Figure 0.

[16] Other disciplinary conceptualizations of drought include hydrological, agricultural and socio-economic drought, each accounting for the effect of rainfall deficits on their respective domain of interest. Hydrological droughts relate to shortages of water in river systems which can be due to meteorological droughts in subsets of the river basins but also to land use changes. Agricultural droughts consider the amount of water available in relation to crop growth. Socio-economic droughts occur when meteorological, hydrological, or agricultural droughts cause economic distress.

In particular, the monthly rainfall estimates for each grid cell were accumulated into annual measures[17]. The annual shortfall from the long term median (for the 1975 to 2006 period) was calculated for each year and each grid cell, and expressed as a proportion of the long term median. Figure 2 shows the proportional deviations from the long run median for the 2001-2006, i.e. the current (2002, 2004, 2006) and preceding VLSS survey years.

Vietnam enjoyed above average rainfall in most of the country in 2001, with only small patches of 20-30 percent below median rainfall in the Mekong River Delta and the Central Highlands. In 2002, however, serious rainfall shortages were observed in large patches of the Mekong River Delta. The Northcentral Coast had a serious drought in 2003, along with less substantial shortages in the Northeastern and Northwestern Uplands. In 2004, the entire nation appeared to suffer from rainfall shortages, with severe deficiencies along the Southcentral Coast and the Central Highlands. This is followed by a year of abundant rainfall in 2005 with only very small patches of shortfalls. Finally, 2006 shows moderate and severe drought along the Northcentral and Southcentral Coastal regions, as well as the Northwestern Uplands and the Red River Delta. The wide variation in rainfall within and across localities over the different survey years provides the necessary variation to identify the effects of rainfall deficiency.

Different cut-offs below which a certain shortfall is considered a drought can be identified. Shortfalls of 10, 20 and 30 percent or more were considered. Figure 3 presents the proportion of episodes during 1975-2006 that rainfall was 20 percent or more below the median. Based on this definition areas along the coast and in the Red River Delta appear more drought prone, and to a lesser extent also those in the Mekong Delta.

Localized excess rain maps

Systematic and accurate information about floods at geographically disaggregated levels is notoriously hard to come by or to construct. One of the reasons is that satellite imagery relies on visibility, and during floods there is usually much cloud cover. Radars can see through clouds, but have not been set aside for this purpose. Yet, floods are part and parcel of livelihoods in many parts of Vietnam and it is thus key to explore their welfare effects.[18] This study distinguishes between localized and regional events. Localized events are based on large amounts of rainfall in short periods of time. They may also induce landslides. Regional events arise when rivers exceed their banks, potentially due to heavy rainfall upstream or snowmelt, or in coastal areas following storm surge.

Inspired by Zubair et al. (2006), who use rainfall intensity in a short period to proxy localized flooding, daily rainfall maps were generated, obtained through spatial extrapolation of the daily rainfall records in the rainfall stations (as opposed to the monthly rainfall data used before) using

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[17] Using 4-months rainfall deficits instead, excluding the 4 driest months of the year, yielded very similar maps. Given the existence of multiple cropping seasons in Vietnam, an alternative approach would be to focus on rainfall shortages during particular periods of the year. This was not pursued here, as it would greatly increase the need for location specific information, and thereby reduce the practical applicability of the approach in other settings. Nonetheless, the approach is sufficiently flexible to accommodate such considerations.

[18] Vietnam has 2,360 rivers and streams that are more than 10 km long. Severe floods were recorded in 1945, 1961, 1964, 1966, 1969, 1971, 1996, 1998, 1999, 2000, and 2001. As a result, the government of Vietnam has actively applied a number of flood control methods, including reforestation, watershed protection; dykes; reservoirs for flood regulation; flood diversion, detention and drainage systems.

the inverse distance squared weighting technique.[19] In particular, rainfall was considered excessive in a particular year if it exceeded 300 millimeters, 450 millimeters, or 600 millimeters in any rolling five-day period throughout that year. By using 5-day periods as opposed to monthly data, a more refined picture of localized flooding could be constructed.

The annual occurrence of excess rain across the grid during 2001-2006 is presented in Figure 4. Figure 5 presents the proportion of years the 0.1 degree grid cells experienced at least one episode with more than 300 mm rain in a consecutive five-day period. The Northcentral and Southcentral Coastal regions appear especially prone to excess rain. Localized flooding occurred also in the Red River Delta Region in 2003. More generally, localized flooding appears especially concentrated along the coast. Excess rainfall is however rather rare in the northern uplands and the south (Southeast and Mekong River Delta regions), suggesting that excess rain is closely related to tropical cyclones, and less to riverine floods. Nonetheless, there are also small inland patches with excess rain, spread across the country.

Riverine floods

Given the historical importance of riverine floods in Vietnam and the limited correlation between the geographical distribution of localized floods and the location of the rivers, the localized flood maps were complemented with riverine (and coastal) flood maps constructed from the Dartmouth Flood Dataset (Dartmouth Flood Observatory, 2008). The latter is an historical worldwide flood database spanning 1985-2007 and showing locations of floods and their major causes (monsoonal rain, heavy rain, tropical cyclones). The information is derived from a wide variety of sources including news and governmental reports based on locally gauged and remote sensing observations.[20] Unfortunately, the maps are not very disaggregated (ten by ten degrees in latitude and longitude). In principle, the flooding caused by any of the types of rainfall might have been picked up already by the localized flooding dataset. What would not be picked up is when rainfall in one place is transported by rivers or terrain to another place or when high tides push ocean water inland.

Given the focus here on riverine and coastal floods and to better pinpoint the locations that actually experienced riverine or coastal floods, the DFO flood maps were overlaid with the location of the rivers taken from the Hydroshed project (Lehner et al., 2008). Only the major rivers were mapped as these will have sufficiently large catchment areas exposing the downstream areas they traverse to (non-localized) flooding. Riverine and coastal flood bands were then derived by considering DFO flooded areas within 2, 5 and 8 meters elevation difference from the closest point on the major river or the coast using a Digital Elevation Model from GLOBE (GloBe Task team, 1999).

The recorded riverine and coastal floods using bands of 2 m elevation difference for each year from 2001 to 2006 are in Figure 6. First, there is little overlap over the years between the localized and riverine flood maps, confirming the complementary nature of both flood indicators.

[19] Because the construction of interpolated daily rainfall maps was very data and time intensive, interpolation was limited to the IDW technique only.

[20] Many floods have now also been imaged by satellite or airborne sensors, and many of them have been translated by DFO into maps of inundation events. Yet, as these satellite based maps did not cover all floods, partly because at times the images were obscured by cloud cover and partly because not all floods have been imaged, it was decided not to use this data source to ensure consistency.

Second, there appears extensive flooding in the Mekong River Delta region almost every year. Third, 2005 was likely the worst year for riverine and coastal flooding. Fourth, riverine flooding was further observed on and off in the other regions, in 2002 and 2005 in the northern uplands, in 2003 and 2005 in the Red River Delta region, and in all years, but scattered around the region in the Southcentral Coastal. Consistent with the events during 2001-2006, the historical record shows that riverine floods happen most frequently in the Mekong and Red River Delta (Figure 7).

Cyclone maps

Tropical storms approach Vietnam from the east. They typically arrive during the Southeast and Northeast monsoon (Christiaensen et al., 2009), with 90 percent of them occurring between June and November, and almost half of them coming ashore in the northern part of the country. To generate annual cyclone maps, a GIS dataset of areas affected by hurricane force winds was developed from the UNEP/GRID-Europe (2007a, 2007b) tropical cyclones databases. In particular, the storm track and wind speed data were used to create symmetric polygons about each path, based on the algorithm by Klotzbach and Gray (no date).[21]

The areas exposed to hurricane force wind (of 120 km/hour) in Vietnam between 2001 and 2006 are in Figure 8, and the frequency with which they have been exposed between 1980 and 2006 is depicted in Figure 9. During the first three years, the tropical cyclones did not affect the land much, though the impact was larger in 2004 to 2006, with two separate cyclones with hurricane force winds hitting the country in 2006. The coastal areas in the Northcentral coast and the Northeastern Uplands appear most exposed to cyclones, with hurricane force winds occurring once every five years. Visual comparison of Figures 4 and 8 suggests that heavy rainfall was caused by the cyclones in some cases, though not in all. There appears less correlation between coastal and riverine flooding and cyclones. Not only do the localized and riverine flood variables not capture the wind damage associated with cyclones, they also overlap only partially with the cyclone paths, underscoring the need to use an additional measure to reflect damages associated with cyclones.

3 Identifying Welfare Effects from Natural Disasters

The effects of natural disasters and other shocks on household welfare are commonly assessed by augmenting a standard reduced form consumption regression with explicit measures of the disasters themselves:

$$\ln c_{ict} = X_{ict}\beta \quad + ND_{kct}\gamma_k + (X_{it} \otimes ND_{kct})\phi + \varepsilon_{ict} \tag{1}$$

where c_{ict} is a measure of consumption for a household *i* in cluster *c* at time t, *X* represent a series of household, cluster and regional characteristics that determine the level of consumption, *ND* are (stochastic) measures of (covariate) natural disaster k in cluster c at time t, ε is a residual term.

[21] The storm track dataset (UNEP/GRID-Europe 2007) had some missing wind speeds. These were filled in using values obtained by regressing known winds speeds on pressure, pressure squared, and dummy variables for hurricane monitoring centres. The R-squared was above 0.91, giving confidence in the predictive power of the data and the regression.

Estimation of γ_k yields an estimate of the average effect of natural disaster k on household consumption. Yet different socio-economic groups are likely to be affected differently either because they are less/more exposed to the disaster ex ante or because they are better/worse able to cope with it ex post. For example, farm households with irrigated fields are less likely affected by droughts than those without, and the more educated may be better able to cope with natural disasters ex post. Similarly, the reception of disaster relief or food aid may lead one to (erroneously) conclude that there were no welfare losses associated with the disaster, even though they induced substantial budgetary outlays elsewhere (by the local or national government) (Yamano, Alderman and Christiaensen, 2005). To explore such heterogeneity in damage or the existence of indirect/hidden welfare losses, natural disasters are interacted with different household and community characteristics and assets ($X_{ict} \otimes ND_{kct}$).

Much of the empirical literature has so far assumed natural disaster measures to be exogenous. Not only does this depend on how they have been measured (objective versus subjective, as discussed above), even when objective measures are used, they may still yield biased estimates. The occurrence of a natural disaster in a locality is likely correlated with the likelihood of it occurring in the first place, which may in turn affect the level of consumption, e.g. through accumulated asset loss at the household and/or community level. Moreover, households in localities that are frequently plagued by natural disasters have likely adapted to these circumstances (for example by adopting more disaster resistant, but less remunerative portfolios (Dercon, 1996), or at times even by building successful livelihood systems around it—"living with floods"). The use of panel data provides the cleanest way to protect welfare estimates of natural disasters from (time invariant) unobserved heterogeneity across communities. However, sufficiently long panels of communities are usually not available for large geographical areas, let alone countries. Within community estimators are usually also less efficient given the lower signal-to-noise ratio, especially when panels are short. This in turn may lead to the disproportionate acceptance of the null-hypothesis of no welfare effect.

Here, repeated cross sections are used instead. To mitigate potential bias from unobserved community heterogeneity, a comprehensive set of socio-economic and agro-ecological characteristics of the locality is included. Most importantly the likelihood of the occurrence of different disaster types is controlled for, omission of which is identified as the major cause for biased estimation of the coefficients on natural disasters. Explicit inclusion of disaster exposure further permits exploration of the occurrence of adaptation. In particular, disaster incidence is hypothesized to mitigate the immediate effect of a particular disaster if households have reverted to low-risk, low-return activities. They are likely to suffer less when disasters hit, and benefit less if there is a rebound, for example due to accelerated replacement of the capital base with more productive equipment.

Empirical analysis of the effects of shocks on household welfare is often predicated on the assumption that the observations are independent from each other, thereby also abstracting from spatial correlation. But in many cases, it seems more likely that observations that are "near" in a geographic sense either influence each other more so than an observation that is far, or that they are more influenced by the same unmeasured force than an observation that is far. This seems especially relevant in a study of natural disasters, where their effects on welfare may permeate across locations especially when product (e.g. food) and/or factor (e.g. labor) markets are integrated.[22] Ignoring such interactions may lead to inefficient and sometimes even inconsistent estimates. [23]

Two types of spatial models are considered: 1) a spatial lag and 2) a spatial error. In the spatial lag model, the dependent variable (consumption in this case) is correlated among neighbors. In the spatial error model, it is the unknown residual that is correlated. Ignorance of spatial lags yields biased estimates, while ignorance of spatial errors reduces efficiency. The full spatial model (also denoted SAC), which combines both forms of spatial correlation, is given by

$$\ln c_{ict} = \rho_1 W_1 lnc_{ict} + Z_{ict}\zeta + \varepsilon_{ict} \text{ with } \varepsilon_{ict} = \rho_2 W_2 \varepsilon_{ict} + u_{ict} \qquad (2)$$

where u_{ict} is iid normal, with mean of 0 and variance of $\sigma^2 V$, when allowing for heteroskedasticity, or $\sigma^2 I$ otherwise) and Z capturing X, ND and its interaction terms. This can be rewritten as $lnc_{ict} = (I - \rho_1 W_1)^{-1} Z_{ict}\zeta + (I - \rho_1 W_1)^{-1}(I - \rho_2 W_2)^{-1} u_{ict}$. Sometimes $W_1 = W_2$; that is, the spatial relations for the lag and error are assumed to be the same. For shorthand notation, define $A = (I - \rho_1 W_1)$ and $B = (I - \rho_2 W_2)$. Equation (2) can then be written as $BAc_{ict} = B Z_{ict}\zeta + u_{ict.}$ The parameters can be estimated by maximizing the log likelihood function:

$$lnL = -(n/2)ln(2\pi) - (n/2)ln(\sigma^2) - (1/2)ln|V| + ln|A| + ln|B| \qquad (3)$$

$$-(1/2\sigma^2)(Alnc - Z\zeta)'B'V^{-1}B(Alnc - Z\zeta)$$

The key difference with the standard log likelihood function[24] is that it also requires calculation of the log determinants of A and B, since these are part of the Jacobian.

One kind of spatial error that has attracted a lot of attention in household survey analysis is the spatial error related to the clustering in the survey design (Deaton, 1997). To accommodate this within the maximum likelihood framework considered here[25], a different weight matrices W_c is introduced, with two different multipliers ρ_{c1} and ρ_{c2}, which together define the spatial error *and* spatial lag of the within cluster observations.[26] As a result, A and B in (3) are replaced by *A* = (I –*

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[22] Trung et al. (2007) find little spatial integration of paddy markets between North and South Vietnam, but a substantial degree of spatial price transmission within the North (Red River Delta) and South (Mekong Delta). See (Mueller and Osgood, 2009) for the transmission of the effects of natural disasters through the labor market.

[23] The contemporaneous spatial relationship between observations is typically specified using (row standardized) weights matrices. The weights matrix tells how observation *i*, represented by values in row *i*, relate to another observation *j*, given in column *j*. By convention, the weights matrix assumes that the weight of observation *i* on observation *i* is 0 for all *i*. Most analyses assume many zeroes in the weights matrix. In part, this is because the direct interaction between distant observations is expected to negligible. Row normalization means that each row is normalized so that it sums to 1. The spatial parameters can then be interpreted as correlation measures, which in analogy to time series, could range from -1 to 1 (an in most spatial analyses, would be expected to range from 0 to 1).

[24] The log-likelihood function associated with (2) can be written as $lnL = -(n/2)ln(2\pi) - (n/2)ln(\sigma^2) - (1/2)ln|V| - (1/2\sigma^2)(lnc - Z\zeta)V^{-1}B(lnc - Z\zeta)$

[25] Fortunately, Stata allows for weighting and clustering in most of its regressions, and we will take advantage of that capability whenever it is available.

[26] To see this, note that the variance matrix for a single cluster consisting of 3 surveyed households might be given by $\begin{matrix} \sigma_\varepsilon^2 + \sigma_c^2 & \sigma_c^2 & \sigma_c^2 \\ \sigma_c^2 & \sigma_\varepsilon^2 + \sigma_c^2 & \sigma_c^2 \\ \sigma_c^2 & \sigma_c^2 & \sigma_\varepsilon^2 + \sigma_c^2 \end{matrix}$ where σ_ε^2 is the variance of each individual element and σ_c^2 is the

$\rho_1 W_1 - \rho_{c1} W_c)$ and $B^* = (I - \rho_2 W_2 - \rho_{c2} W_c)$, with W_c the weights matrix for clustering, with zero on its diagonal, just like the other weight matrices. In doing so, the method also improves upon most statistical packages like Stata. They typically use a modified Huber-White estimator for the variance estimator in the case of clustering rather than trying a maximum likelihood solution. In doing so, they do not allow for a direct impact of intra-cluster neighbors' dependent variables. It is assumed that there is no spatial lag from the cluster variables. This assumption can be tested, but it is not necessarily a good assumption to make *a priori,* as the existence of spatial lag can introduce omitted variable bias.

Finally, to increase precision in estimating the welfare effects of natural disasters, the multiplicative heteroskedastic specification advanced by Just and Pope (1978, 1979), is adopted: $u_{ict} \sim N(0, \sigma_{ic}^2)$ with $\sigma_{ic}^2 = \sigma^2 \exp(\mathrm{Z_{ict}}\alpha)$. Explicit specification of the heteroskedastic nature can be accommodated in the likelihood framework and also helps shed some light on the correlates of the conditional (idiosyncratic) variance of consumption. These can be of interest in themselves (see Christiaensen and Subbarao (2005) for an application in the context of estimating household vulnerability).[27] The log likelihood estimation function applied to the data thus becomes:

$$lnL = -(n/2)ln(2\pi) - (n/2)ln(\sigma^2) - (1/2)ln|V| + ln|A^*| + ln|B^*|$$

$$- (1/2\sigma^2)(A^* lnc - Z\zeta)' B^{*\prime} V^{-1} B^* (A^* lnc - Z\zeta) \qquad (4)$$

with V a diagonal matrix with $\exp(\mathrm{Z_{ict}}\alpha)$ on the diagonal.[28] Thomas (2010) provides a detailed discussion of the optimization routines developed in Matlab to estimate (4).[29]

covariance within each element of the cluster. The practical difficulty in solving this in a maximum likelihood framework is that this block diagonal matrix needs to be inverted at each phase of the optimization routine. With small household surveys of a few hundred households this might be possible, but for large surveys, this is extremely slow and in many cases it becomes too numerically intensive to run successfully. This is why statistical packages like Stata use a modified Huber-White estimator for the variance estimator in the case of clustering rather than trying a maximum likelihood solution. Yet, using an insight from the spatial approach, the off-diagonal, non-zero elements (i.e., the σ_c^2) can be considered as a type of W matrix specifying that the neighbors are those elements within the same cluster. This avoids having to invert the matrix at each iteration of the maximum likelihood routine. Just to be clear, to follow the convention that W matrices have diagonal elements of 0 (this is okay, because in the spatial approach we also difference a multiple of the W matrix from the identity matrix, thus restoring the diagonal elements), the previous block of the cluster matrix would be given as a W matrix as $\begin{matrix} 0.0 & 0.5 & 0.5 \\ 0.5 & 0.0 & 0.5 \\ 0.5 & 0.5 & 0.0 \end{matrix}$ with standardized row weights summing to 1.

[27] The multiplicative specification proposed here has some particular advantages in this regard as it does not constrain the parameters to affect the conditional mean and variance of consumption in the same direction (Just and Pope, 1979).

[28] Note that the usual Jacobian term of $\frac{1}{2} ln\sigma_{ic}^2$ would be $\frac{1}{2}\ln\,[\exp(Z_{ic}\alpha)]^2 = Z_{ic}\alpha$

[29] The optimization routines were written in Matlab and are available from the authors upon request.

4 Toward an Empirical Application

The socio-economic data to estimate equation (4) were obtained from the Vietnam Household Living Standard Surveys (VHLSS) of 2002, 2004, and 2006. In each round, households were selected using a 3-stage sampling process.[30] These three survey waves provide high quality and nationally representative household information on household consumption and income, their demographic characteristics, health status, educational achievements, asset holdings and the availability of public services in the community. The latter is obtained from the community survey which was fielded in parallel to the household surveys. The questions in the VHLSS were similar throughout the different surveys rendering them highly comparable. The surveys were conducted each year between May and November of the survey year, with expenditures referring to the past 12 months.

Real total per capita expenditure less per capita expenses on health care is taken as the dependent variable. Health expenditures are subtracted as the study also controls for the effect of idiosyncratic health shocks, proxied by the number of days spent ill in bed over the past year by senior adults, adults and children respectively. Inclusion of health expenditures in the overall expenditure measure, which are highly correlated with illness and not routine or maintenance health outlays, might perversely suggest an increase in welfare following sickness. The expenditure data are expressed in January 2002 prices using the CPI provided by the Government Statistical Office. They are also corrected each year for regional and rural/urban differences across the 8 regions.

A series of standard household demographics (household size, the dependency ratio, the age, gender, educational status of the household head[31]) are included to control for household characteristics in determining a household's consumption level. In this context, controlling for ethnicity is especially important as poverty is increasingly concentrated among ethnic minorities, often located in Vietnam's mountainous areas. While productive assets affect the capacity of a household to generate income and thus its consumption level, current asset levels may be simultaneously determined with consumption, as the disposal of assets (e.g. livestock) may be relied upon to cope with disasters, or they may reflect destruction by the disasters, leading to an underestimate of the welfare effects of the latter. In the absence of information of asset ownership prior to the survey, only those assets that display limited variation over time were included such as the amount of land owned and an indicator variable indicating whether the household owns a house or not.

[30] Communes (the primary sampling units) were selected in the first stage with a probability proportionate to population size based on the 1999 Population census. On average, a commune contains 1,600 households. Subsequently, three enumeration areas (EAs), containing about 100 households each, were randomly selected within each commune. One of these EAs would be used to draw a sample of households in each VHLSS during the final (third) stage. In, 2002, this resulted in a sample of 29,530 households across 2,910 communes (EAs) (25 households per EA in 75% of the EAs and 5 in the remaining 25%). In 2004 and 2006, three households were selected per EA, resulting in 9,189 households each year in 3,061 communes. Phung and Nguyen (2008) provide a detailed description of the questionnaire and survey design.

[31] 0 refers to no degree, 1 to primary school, 2 to lower secondary school, 3 to higher secondary school, 4 to short-term technical worker, 5 to long-term technical worker, 6 to professional secondary school, and 7 to college diploma and above.

To reflect access to public services, indicator variables are included that take the value of one if clean water[32], sanitary latrines,[33] or electricity are present in the community, and zero otherwise. To proxy a household's integration in the overall economy, the community data were further augmented with the distance of the centroid of the community (in meters) to the nearest part of the nearest primary or secondary road, as designated in the VMAP0 dataset (NIMA 1997). These measures were computed that using Arc View 3.2. In addition, the estimated travel time to the nearest town or city of at least 25,000 people, the nearest city of at least 100,000 people, and the nearest city of at least 500,000 people were included. The travel times were computed in Arc View from a friction grid that assigned differing travel times to various classes of roads, urban areas, water bodies, off-road, and crossing international boundaries.[34]

To further control for geological and agro-ecological characteristics at the community level, elevation figures were included, taken from the GLOBE 1 kilometer elevation database (GLOBE Task Team et al. 1999). Elevation differences were also incorporated as a measure of terrain roughness. These were computed using the SRTM3 data (Jarvis et al. 2006) by subtracting the minimum elevation in a 1 kilometer grid from the maximum elevation in the 1 kilometer grid. Finally, urban/rural and regional indicator variables help capture unobserved (time invariant) location specific characteristics related to the urban and rural livelihood systems as well as those related to regional variation in the agro-ecological, economic and political environment. Year dummies were included to control for the survey year.

The disaster data were mapped into the household survey data at the commune level, which are on average only 30.3 kilometer squared.[35] More precisely, the centroid for each commune was identified and given the highly covariate character of the different disasters, the state of nature observed at that point in the disaster maps was assumed to be the state of nature experienced by all the VHLLS households in that commune. It emerges that while most households have some limited drought risk, twenty percent of the population has at least 30 percent chance of being flooded each year (Chart 1). At the same time, about two fifths of the population will never be affected by a flood and storms pass by about half the population.

Given the concentration of flood events, it does not come as a surprise that there is a strong intertemporal correlation in the occurrence of floods (0.44 for flash floods and 0.55 for riverine floods), i.e. households experiencing a flood his year also have a high chance of experiencing one the following year (Table A2). As expected, there is also a correlation between the statistical frequency

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[32] Two sources of water are typically distinguished in Vietnam: water for direct human consumption (drinking, cooking), and water for sanitation and maintenance purposes (washing clothes and bathing). Water is considered clean if it comes from (1) private tap water inside the house, (2) private tap water outside the house, (3) public tab water, (4) water pumped from deep drill wells, (5) water from hand-dug and reinforced wells, (6) rain water, (7) purchased water, or (8) water from a water tank.

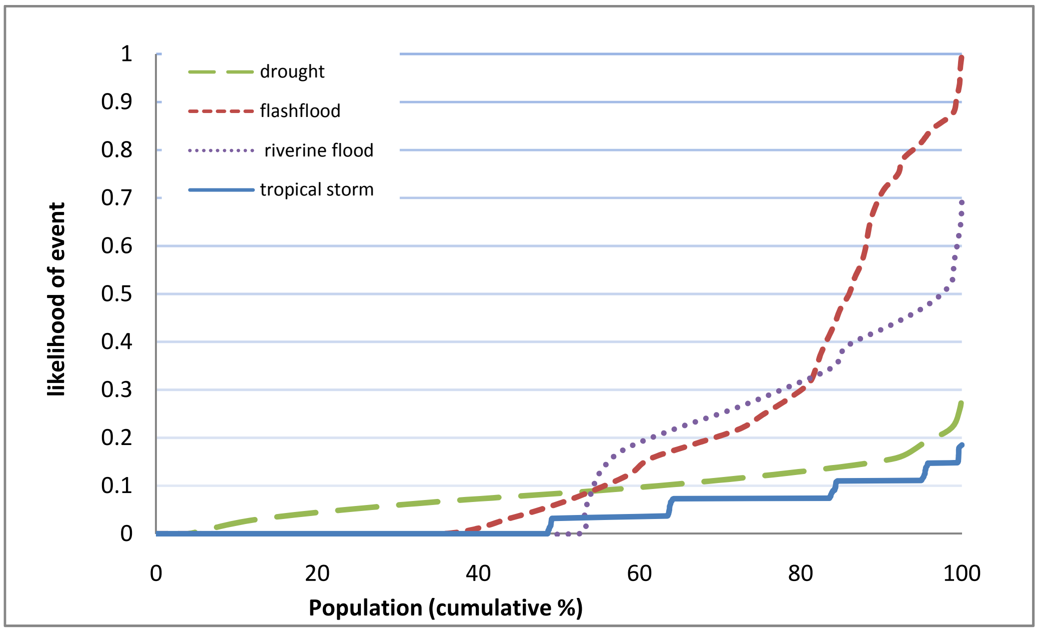
[33] Sanitary latrines include flush toilets with septic tank/sewage pipes, suilabh toilets, and double vault compost.

[34] The VMAP0 (NIMA 1997) was used to obtain data on three classes of roads: 1) divided highways; 2) primary/secondary roads; 3) paths or trails. For rivers and lakes, the CIA World Data Bank II (CIA 1972) was used. The population centers are from the GRUMP settlement points dataset (CIESIN et al. 2004a) and the World Gazetteer database (Helders 2005). Urban boundaries are from the GRUMP urban extents database (CIESIN et al. 2004b). The international boundaries are from the World Bank mapping office.

[35] To maintain confidentiality, the geographic coordinates of each household in the VHLSS are not made publicly available, only the shapefiles for the different communes surveyed.

with which extreme weather events happen (their incidence) and their actual occurrence during the current or previous survey years, a correlation which is most pronounced for floods. Finally, some bunching of events is also observed, with households subjected to a hurricane, often also hit by flash floods, as indicated by the correlation coefficient of 0.55 between the incidence of flash floods and the incidence of hurricanes. Hurricanes thus manifest themselves partly through localized flooding. Riverine floods on the other hand appear negatively correlated with flash floods and hurricanes. Finally, note that a higher incidence of drought does not exclude the occurrence of floods within the same year as indicated by the positive correlation between the incidence of droughts and floods (and hurricanes).

Chart 1: Most people are exposed to droughts, but infrequently; floods affect a sizeable population often, and a large population never; hurricanes pass by most and infrequently affect others.



The bunching of the disasters underscores the importance of considering their effect separately, but jointly in the regression analysis. Potential persistence in the effect is examined through consideration of both the current and one year lagged events. Finally, to separate out the potential effects of adaptation from the immediate welfare effects from current events, the regressions also control for the frequency with which the different events occurred.

5 Welfare Effects of Natural Disasters in Vietnam

To benchmark the results, Table 1 (column 1) presents the estimated OLS coefficients[36] of a standard consumption model augmented with information on the present and lagged occurrence of

[36] These were obtained from the pooled 2002, 2004, and 2006 VHLSS data with standard corrections for heteroskedasticity and clustered survey design using the Hubert-White estimator provided in STATA.

the different extreme weather events (droughts, localized and riverine floods, hurricane force winds). These are subsequently augmented with data on the frequency of their occurrence (column 2) and interaction terms between the extreme events and the distance to cities with more than 500,000 inhabitants to capture geographical diversity in the effects (column 3). The Maximum Likelihood estimates which also correct for spatial correlation (in addition to heteroskedasticity and cluster design) are in column 4. The following cut-offs were settled on to identify an event as extreme: rainfall 20 percent below the long run median for drought; at least one episode of more than 300 mm rainfall in 5 consecutive days for excess rain/localized flooding; DFO recorded floods within 2 m elevation difference from the major rivers or coast line; and areas affected by 65 knot (or 118 km/hour) hurricane wind force.

The regressions display high explanatory power (R-squared between 55 and 60 percent) and the estimated coefficients on the different household and community characteristics are consistent with those reported in the literature. This provides confidence in the base results.[37] Larger households with more dependents and belonging to ethnic minorities are poorer, while the more experienced and more educated households with more land and in possession of a house enjoy higher living standards. Illness of adult household members (not for children or elderly) tends to be negatively associated with consumption levels, though it is only statistically significant for the spatially corrected ML estimates. Households in communities with better sanitary conditions (sanitary living water and sanitary latrines) and better road access are also richer, while households located on steeply sloped areas tend to be poorer. Households in urban areas are on average about 30 percent richer, with levels of consumption declining the further away from the urban center and the gradients steepening the larger the urban center. Consistent with the steep GDP growth observed in Vietnam during the survey period, household consumption levels (in real terms) increase substantially between the survey years, as reflected in the large and statistically significant coefficients on the year dummy variables.

The more exposed to natural disasters, the poorer households tend to be.

Turning to the welfare effects of weather events, household welfare is substantially affected by natural disasters, but at first sight, not always in the direction expected. When included without controls for exposure (Table 1, column 1), current droughts, localized and riverine floods appear positively correlated with household welfare, with the occurrence of a localized flood last year also increasing welfare, with the lagged effects of riverine floods exercising a dampening effect on household welfare. However, when the frequency of extreme events in each locality is included together with their interaction with the current and lagged occurrence of the event (column 2), a different picture emerges.

Welfare is lower in areas frequently exposed to droughts and hurricanes, while (surprisingly) it appears to increase welfare in areas frequently exposed to excess rain, with no discernable effect in frequently inundated riverine areas. Second, the direction of the immediate welfare effects of current and lagged events also changes when interacted with the frequency of their occurrence.

[37] The comprehensive controls for community (and household) characteristics help protect the natural disaster variables from omitted variable bias. As the survey comprises more than 3000 communities, each surveyed at least two times, overfitting is not considered a concern. Note also that the number of controls is in effect still substantially less than when estimating a household or community fixed effect regression.

Current droughts, localized and riverine floods no longer increase welfare and excess rainfall in the current year is now negatively related with consumption, at least when excess rain is not a regular phenomenon. The signs and statistical significance of past weather events, reflecting the lagged welfare effects, also change when they are interacted with their frequency.

Frequent exposure may induce the adoption of low risk, low return portfolios (Eswaran and Kotwal, 1990; Rosenzweig and Binswanger, 1993), but the associated welfare loss could also reflect accumulated asset loss (Carter and Barrett, 2006), issues further discussed below. Poor people may also concentrate in areas considered too risky to live in. Given the myriad of household and environmental controls that already capture household wealth, such as education, ownership of land and housing, access to public infrastructure and amenities, proximity to urban centers as well as agro-ecological conditions (elevation and slope), the latter interpretation of the results is less likely. The results in columns (1) and (2) underscore especially the importance of controlling for the frequency of exposure in studying the immediate and lagged welfare effects of natural disasters.

Those further away from large urban centers are poorer, but also tend to suffer less from being regularly confronted with natural disasters.

The welfare effects likely also differ depending on the proximity to large urban centers (Table 1, column 3). In particular, interaction of the different events with the distance (in tenths of hours) to cities with more than 500.000 inhabitants suggests that the welfare effects gradually change away from these large urban centers, with locations further away typically less affected. For example, while areas frequently hit by drought are less wealthy, frequent exposure to droughts appears less damaging in terms of welfare loss further away from the large cities, that is, after controlling for the welfare reducing effect of living far away from urban centers. Similarly, areas located in storm prone areas further away from the urban centers are less affected than those in storm prone areas close to the city. A similar phenomenon is observed when it comes to localized flooding –with frequent exposure less damaging among those further out.

Economies and livelihoods become more rural and agriculturally oriented further away from the metropolitan areas. Asset holdings and the share of agricultural land irrigated typically declines (Table A3) and the support systems weaken. In particular, households further away tend to be less likely to receive remittances from abroad and the amounts received tend to be smaller. And while they are as likely to receive domestic remittances and even more likely to receive disaster relief, the latter is still rare (only 12 % of the households received disaster relief during the 2002-2004-2006 surveys) and it usually comes in much smaller amounts than the relief received by those close to the metropolitan centers. Taken together these descriptive suggests that households further away are not only more exposed ex ante (at least to drought) but also have lower capacity to cope with natural disaster ex post (less assets/savings and less effective support systems). This may have induced them to adopt portfolios that are more resilient to damage from natural disasters, though portfolios that are also less remunerative, as indicated by the steep declining gradient in household welfare as one moves away from the metropolitan centers.

From this perspective, the reverse finding on riverine flooding comes as a surprise. Out of the 4 disasters considered, only frequent exposure to riverine flooding is associated with an increase (as opposed to a decline) in living standards, with its benefits declining as one moves away from the major metropolitan centers. In this case, regular flooding seems to have induced a superior livelihood system, at least among those closer to the metropolitan area. It concerns here largely households in the Mekong River Delta, who have their livelihood systems built around floods ("living with flood", very much as in Bangladesh (Beck, 2005)). Comparison of self-reported flood measures with the riverine flood measure used here (taken from the DFO) supports this interpretation. The flood incidence based on the latter measure is much larger than the flood incidence based on the former, indicating that not all floods recorded in DFO are actually also experienced as negative events by the households themselves. It is not so much the flooding as such which is detrimental, but rather its duration and level, rendering only a subset of the DFO observed floods really damaging.

Immediate, lagged and persistent welfare effects by event

For a more detailed shock by shock comparison of the welfare effects, the study turns to the Maximum Likelihood welfare estimates, which also correct for spatial correlation (Table 1, column 4). While they qualitatively correspond to the OLS estimates in column 3, the size of the effects changes at times substantially and the coefficients are also more precisely estimated, yielding additional insights. This is expected given that both the tests for spatial lags and errors (not reported here) point to the existence of spatial correlation (within and beyond the cluster). To provide some further intuition to the findings, it is simultaneously explored how households cope with each of the shocks. In particular, the immediate, lagged and persistent effects of the different natural disasters on a household's asset holdings, its reception of official disaster relief and domestic and foreign remittances, and its degree of income diversification as captured in the Herfindahl index,[38] are given in Table 2. The effects of natural disasters on asset holdings and income diversification are estimated using OLS with suitable corrections for heteroskedasticity and cluster design, while left censored tobits are used for the household assistance regressions, as many households did not receive any assistance/remittances. To control for household, community and environmental characteristics, the same controls are used as in the household welfare regressions above. The ML results are repeated in the first column (Table 2, column 1) to facilitate the discussion.

Droughts reduce welfare, though mainly among those with few irrigated plots.

As before, there are no statistically significant signs of immediate or lagged effects of droughts. Further investigation using the 2004 and 2006 survey years for which information on irrigation is also available, shows that irrigation provides effective protection against droughts. In particular, households with no irrigated plots see their per capita consumption decline by 16 percent on average the year of the drought, while those with all their plots irrigated (the majority of the sample) experiencing only a 3 percent loss in welfare. In other words, irrigation proves quite effective in protecting households from drought. No lagged effect of droughts is observed. Self-insurance through asset disposal (which shows up with a lag (Table 2, column 2)) and income diversification (lower Herfindahl index), especially in drought prone areas, enable households to further soften the blow of immediate drought shocks. Yet, this also erodes their asset base over time, consistent with the lower welfare observed in drought prone areas. The loss can be

[38] The Herfindahl index is a measure of income diversification, defined as the sum of the squares of the different income shares. It ranges between one and zero, with 1 indicating full specialization and lower values pointing to increasingly diversified income portfolios.

substantial—households in areas with a 10 percentage point higher frequency of drought are on average 12 percent poorer—though the majority of households only experience a drought once a decade, with only two percent facing a drought every three to five years.

Interestingly, the welfare loss associated with frequent drought occurrences declines as one moves away from the metropolitan areas. This is likely related to the somewhat larger responsiveness of official relief efforts to current drought events in those more remote areas (albeit with lower amounts disbursed on average),[39] which appears to mitigate the need for self insurance through asset disposal, as suggested by the lower asset loss experienced in less urbanized areas (positive coefficient on the interaction term of lagged drought and distance to large city—column 2). Over time this yields lower accumulated asset loss in the more remote areas (column 2) and less severe welfare loss (column 1) than in the areas closer to the metropolitan areas. The disaster relief systems appears to enable these households to remain more specialized (higher Herfindahl index), i.e. more agriculture focused, than those in other drought prone areas closer to the metropoles, suggesting that the relief efforts also help in mitigating the effects of droughts, even though the amounts disbursed tend to be smaller than among those closer to the metropoles.

Localized floods cause an immediate welfare loss, which households largely recuperate thereafter.

Heavy rainfall has an immediate welfare reducing effect, by 7.7 percent on average (Table 2, column 1), likely through the destruction of assets (Table 2, column 2), though less in areas, which are frequently exposed, and thus better adapted, or those further away from the metropoles. There is also a lagged welfare increasing effect of heavy rainfall. Heavy rainfall often goes hand in hand with landslides which can cause substantial damage to infrastructure, property and capital. When not too severe or not too frequent, households can take advantage of such asset loss to accelerate replacement of their assets by better, more productive ones, accelerating their return to their normal growth path, as postulated in the vintage capital growth models (Hallegate and Dumas, 2009). Households in areas more frequently affected by localized floods tend to experience lower levels of consumption, though again, less severe so among those in flood prone areas further away.

Overall the welfare losses from frequent exposure to excess rain are only one fourth to one fifth (-0.28/-1.26) those brought about by regular exposure to rainfall shortages. Lower net asset loss (the immediate negative effects largely compensated by technically better replacements in the next period helps understand the difference in the welfare effects of rainfall shortages and rainfall excesses (Table 2)). While the destruction of assets associated with excess rain does not lead to higher welfare levels altogether, their replacement with better more productive alternatives, especially in areas that are not frequently confronted with excess rain (see the negative coefficient on interaction term of lagged localized flood and excess rain frequency in column 2) can mitigate their negative effects. Droughts on the other hand, do not induce an immediate asset loss as such (beyond livestock loss). Assets are disposed off to cope with the shocks, smoothing consumption in the current period, but eroding the household's coping capacity over time, consistent with the larger negative effect of the frequent occurrence of droughts on asset holdings (coefficient equals -3.4, the largest among all disasters considered), and by extension on consumption. Larger official relief

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[39] Indicated by the jointly positive and statistically significant coefficients on current drought events and their interaction term with distance away from the metropolitan areas when 2 hours or more away from the metropolitan area.

efforts in frequently flooded areas closer to the larger cities may further attenuate the welfare loss compared with those related to water shortages. Households do not appear to change their income portfolios in response to heavy rainfall—none of the coefficients on the localized flood variables and their interaction terms are statistically significant, with the exception of one, whose coefficient is very small.

While households learned to live with riverine floods, severe floods can cause substantial damage.

The occurrence of a riverine flood reduces household welfare on average with a combined 23 percent, by 5.8 percent immediately and by 17.2 percent in the subsequent year, indicating that it takes some time for the full effect to be felt. But as indicated above, not all riverine floods recorded in DFO make for a negative experience, and households in areas prone to riverine floods appear on average even slightly better off. They experience less immediate welfare loss (positive coefficient on interaction term between flood frequency and current flood event—column 1, Table 2) and dispose less of their assets to cope with the effects (positive coefficient on interaction term with lagged riverine flood – column 2, Table 2), likely linked to the much better provision of disaster relief in regularly flooded areas. While the disaster relief in the flood prone areas prevents the erosion of the asset base (no loss of assets in frequently affected areas—column 2), it is nonetheless not sufficient to prevent a substantial 17 percent temporary reduction in their consumption welfare loss based on the floods recorded in this sample. This loss manifests itself with a lag, together with lagged reduction in the asset base.

Households in flood prone areas away from the urban centers on the other hand appear more negatively affected by riverine floods. They receive much less disaster assistance, find themselves over time with a lower asset base (negative coefficient on interaction distance to city and flood frequency), resulting in a long term welfare loss (negative coefficient interaction term distance to city and flood frequency—column 1). Households also cope with the lagged effects of shocks through income diversification, especially closer to the cities.

Hurricane force winds inflict immediate and lasting damage to household welfare.

The occurrence of a hurricane is associated with a 52 percent immediate welfare loss inside cities with more than 500,000 inhabitants, a potential 16 percent loss in the subsequent year, and a 20 percent reduction in welfare in areas with a 10 percentage point higher chance of being hit by hurricane wind forces. Furthermore, unlike with (localized and riverine) floods the immediate effects are not mitigated in areas that are more frequently hit, i.e. there is no adaptation. Rather the opposite, the immediate and lagged effects are, if anything, even more detrimental, indicating that households have not been able to adapt to and that the official disaster relief system has not been effective in dealing with hurricane forces winds in Vietnam. Second, the damage is less severe the further away from the urban centers. This can be expected given the larger concentration and reliance of the economy and livelihoods on infrastructure in the more urban economies. Official and private transfers have largely been unresponsive to storm related disasters (columns 3-5, Table 2). Similarly portfolio choice remains largely unaffected in the face of storms, with the exception of some lagged portfolio diversification in areas frequently affected.

Summarizing the key insights regarding the allocation of disaster relief, one of the key ex post policy responses to disasters, households further away from the larger urban centers (more than 500,000 inhabitants) are on average more likely to receive disaster aid (see positive coefficient on log hours to 500k city). While the amounts received tend to be smaller, it does help in coping with the welfare loss. Furthermore, relief efforts appear not to be sustained much beyond the first year. The disaster relief systems appear especially well developed in frequently flooded areas (both localized and riverine or coastal) close to the major urban centers. Official disaster assistance is not given following hurricane force winds. There are no clear systematic patterns with respect to the reception of domestic or foreign remittances. Sectoral income diversification does not emerge as a major coping strategy, with the exception of the larger income diversification observed in drought prone areas closer to the urban centers. Asset losses, which can result from direct damage or through asset disposal to self insure, often show up with a delay and tend to be less severe further away from the urban centers.

In conclusion, while households largely manage to cope with drought events, often through asset disposal, but especially through irrigation, the frequent occurrence of droughts erodes their capacity to cope with them over time, resulting in a substantial welfare loss among households in drought prone areas closer to the urban centers. Households in drought prone areas further away from the urban capitals also suffer, but less as they manage to hang on to their assets better because of drought responsive relief efforts. Localized flooding exerts an immediate 7 percent toll on welfare though much of that loss appears to be recuperated the next year potentially through replacement of the lost asset base by better more productive ones, at least among those that are not frequently hit. The latter tend to suffer less immediately, partly through the reception of disaster aid, but they also benefit less from the faster adoption of more productive assets, likely resulting in some asset erosion over time and lower consumption levels (though to a lesser extent than in the case of regular rainfall failure). The damage from frequent exposure to localized floods is again less severe among those further away from the urban centers, as they experience less asset loss, while receiving more immediate disaster relief. Riverine floods can cause substantial welfare damage (23 percent), especially among those not frequently exposed, who tend to be better served by disaster relief, at least when living close to the urban centers. Finally, the largest damage is inflicted by hurricane force winds, with both regular exposure and proximity to the urban centers exacerbating the welfare losses substantially.

6 Concluding Remarks

Understanding how natural disasters affect human welfare is an increasingly pressing concern, not least in Vietnam, which ranks among the most disaster prone countries in the world. This study illustrates a methodology to study the welfare effects of such events in a country specific setting using spatially disaggregated disaster maps derived from primary meteorological data combined with nationally representative geo-referenced household survey data. By deriving the spatially disaggregated event and hazard maps directly from the meteorological data, issues of endogeneity in estimating the effect of such events on consumption are mitigated. The event and hazard maps provide also useful tools for policy and project planning. In addition, in estimating the welfare effects, spatial correlation was also accounted for. While the latter is routinely ignored, this is less suitable in empirical examinations of the household welfare effects of spatially disaggregated disasters whose effects regularly permeate the economy through product (food prices) and factor (labor) markets.

The econometric results suggest that households in Vietnam largely manage to cope with the immediate effects of drought events, through irrigation, though that the frequent occurrence of droughts erodes their capacity to cope with them, resulting in substantial welfare loss especially among households in drought prone areas closer to the urban centers, where disaster relief is less pronounced. Localized floods exert important welfare losses, on average an estimated 7 percent, though much of that loss appears to be recuperated through capital replacement in the subsequent year, at least among those who are only occasionally affected by such floods. Those who are frequently affected suffer more, though the long run effects from frequent exposure to localized floods are substantially less than those from frequent exposure to droughts, partly due to a responsive relief system in the more urban areas that are frequently affected. Riverine floods cause substantial welfare damage (23 percent) in the short run, though less so among households who are frequently exposed. Not only do they tend to be much better served by disaster relief, especially when close to the metropolitan centers, it is important to note that not all riverine floods recorded in DFO are experienced as negative events, as households built they livelihood systems around them, especially close to the metropolitan areas. They learned to live with floods. Finally, the largest damage is inflicted by hurricane force winds, with regular exposure and proximity to the urban centers, which both exacerbate the welfare losses substantially.

Overall, the study shows that there is promise in using meteorological data to construct spatially disaggregated weather event and weather hazard maps, the first objective of the study. Such data are becoming increasingly available and natural event and hazard maps have also important direct applications for policymakers beyond their use in estimating the welfare effects of disasters. The fine-tuning and validation of such maps is an important area for further research. Second, there are important long run negative effects of being regularly confronted with natural disasters. Third, short run losses can be substantial, with hurricanes causing most havoc. Fourth, there are signs of adaptation, with frequent exposure to localized and riverine floods reducing the welfare losses associated with these events, partly through the development of effective disaster relief systems. There is however no adaptation to hurricanes, rather the contrary, with high frequency of hurricanes exacerbating the losses from particular events. Fifth, those further away from the large urban centers often enjoy more immediate disaster relief which appears to mitigate the current effects of natural hazards, underscoring the importance of effective disaster relief systems. In the absence of further support systems, they likely also adopted less risky, but also less remunerative portfolios. Sixth, the disaster relief systems have largely eluded areas affected by hurricane force winds so far, an important area of attention Vietnamese policymakers.

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Figure 0: Regions of Vietnam

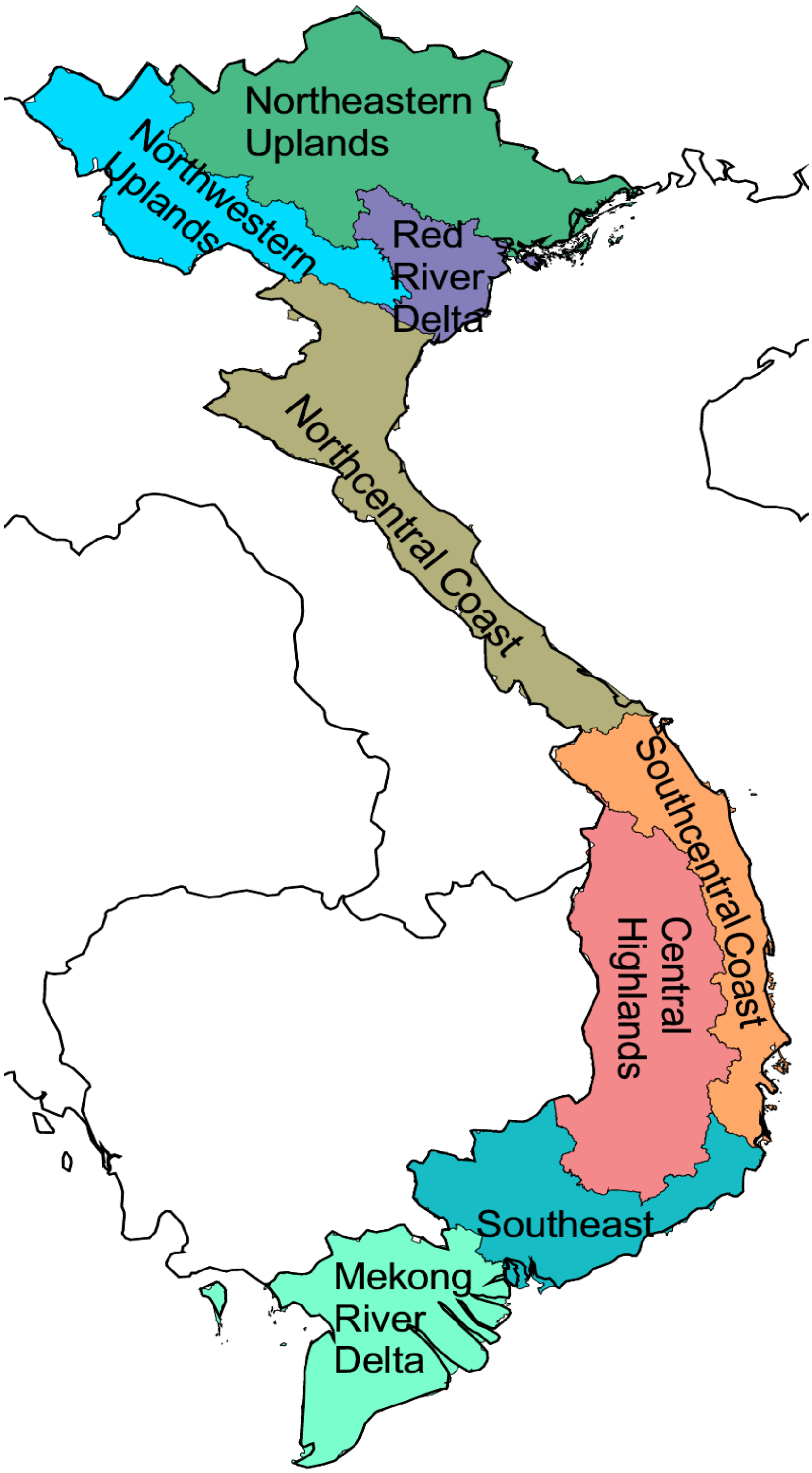


Figure 1: Rainfall maps using inverse distance weighing and inverse elevation difference weighting display close resemblance

Figure 1a: Rainfall prediction using inverse distance squared from 5 nearest station data only, June 2006

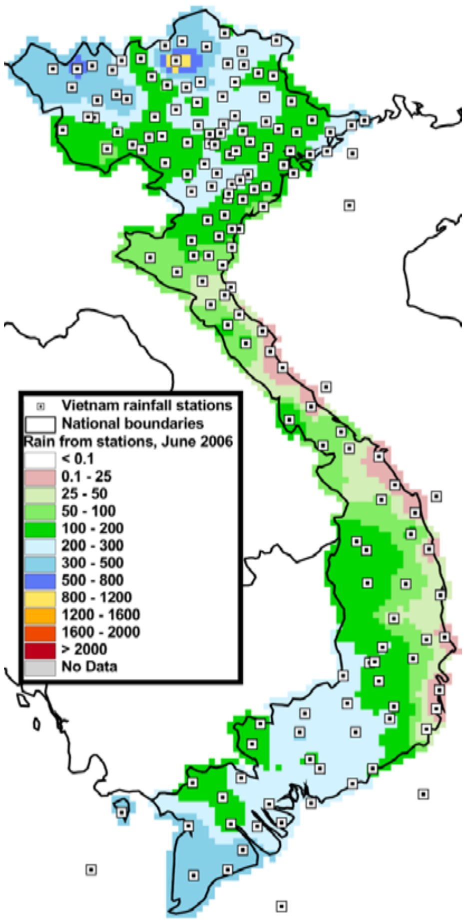


Figure 1b: Rainfall prediction using elevation difference weighting for 10 nearest stations only, June 2006

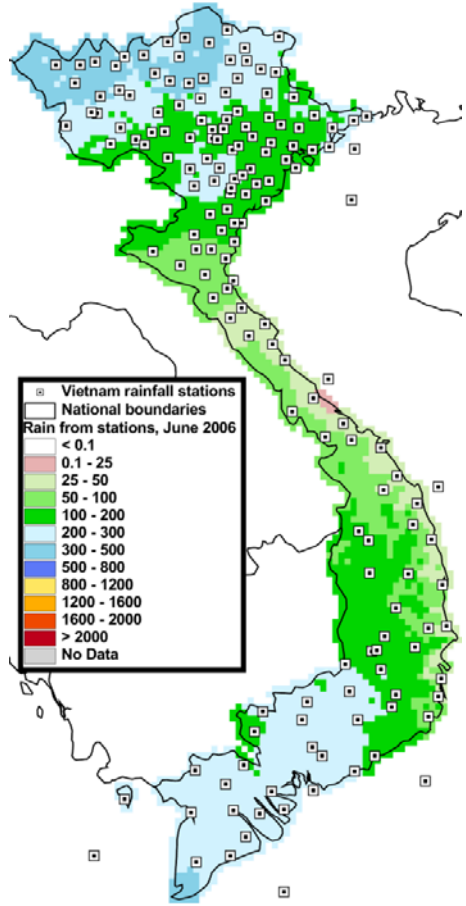


Figure 1c: Rainfall prediction from regression analysis, June 2006

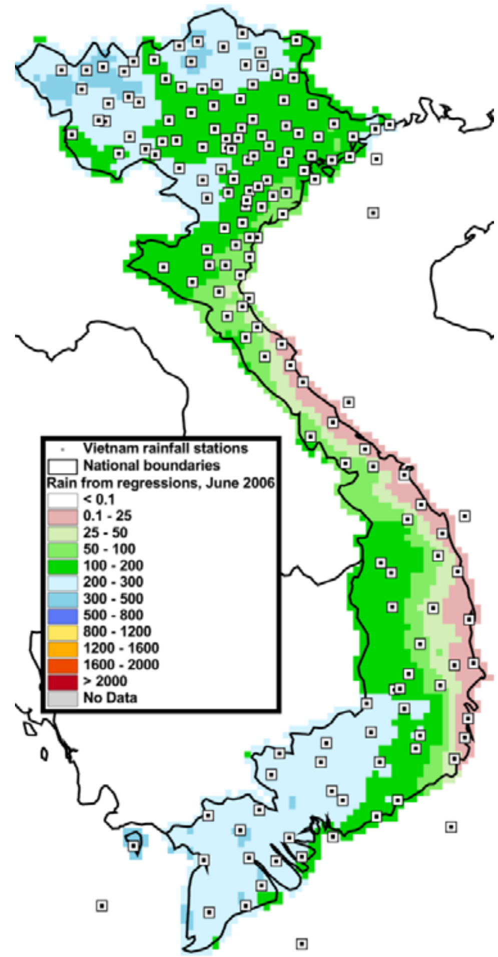
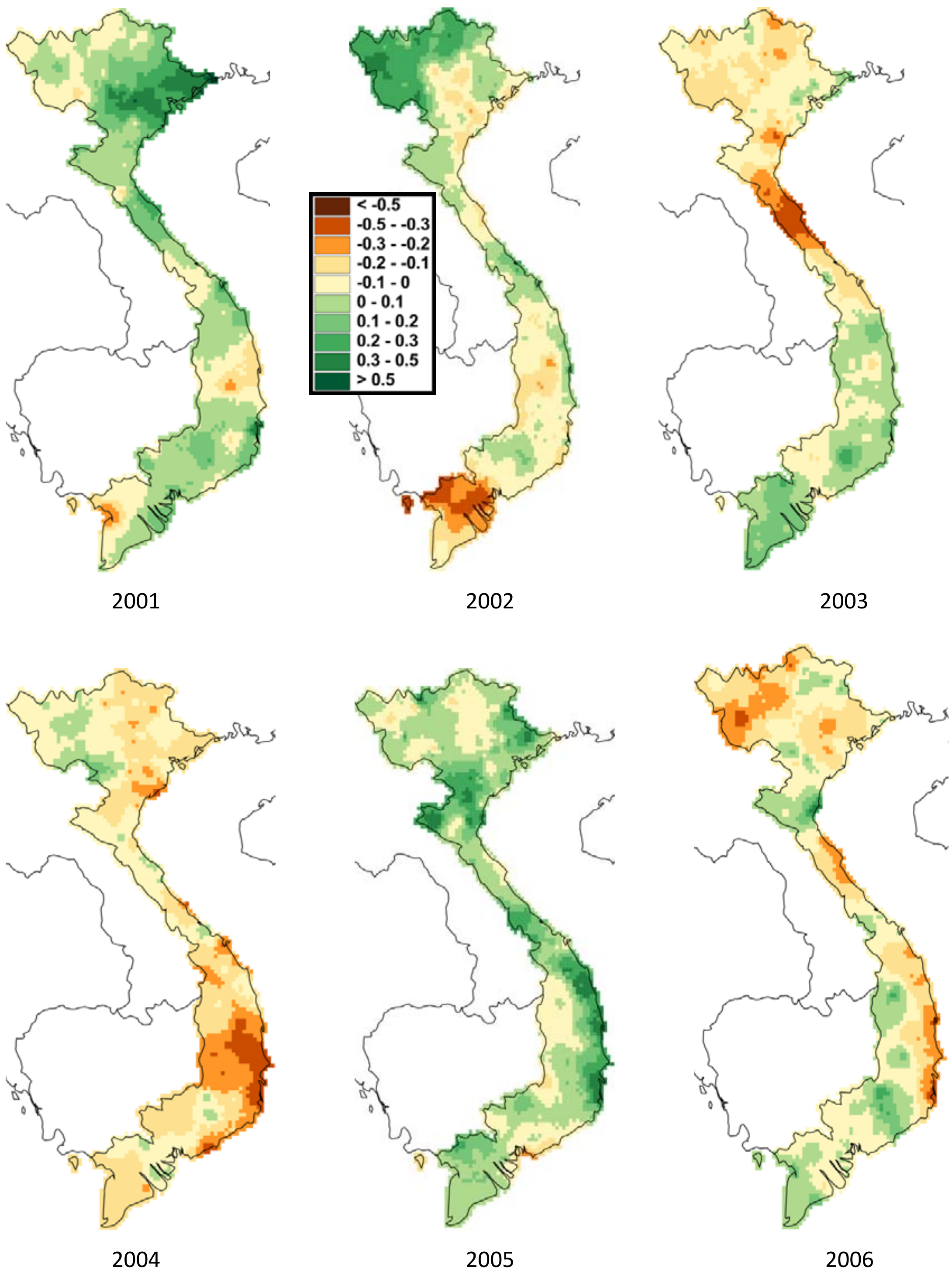
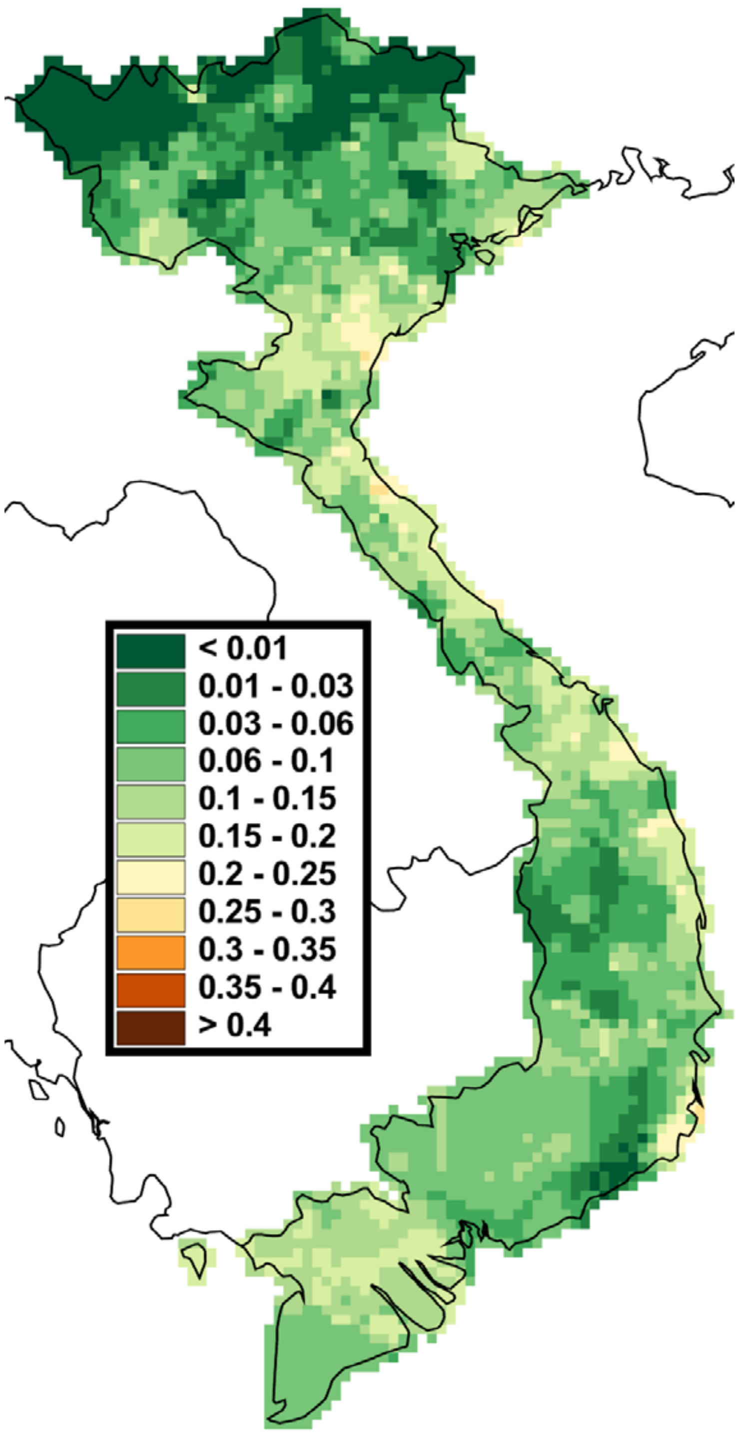


Figure 2: Deviations from median annual rainfall for each year 2001 to 2006.



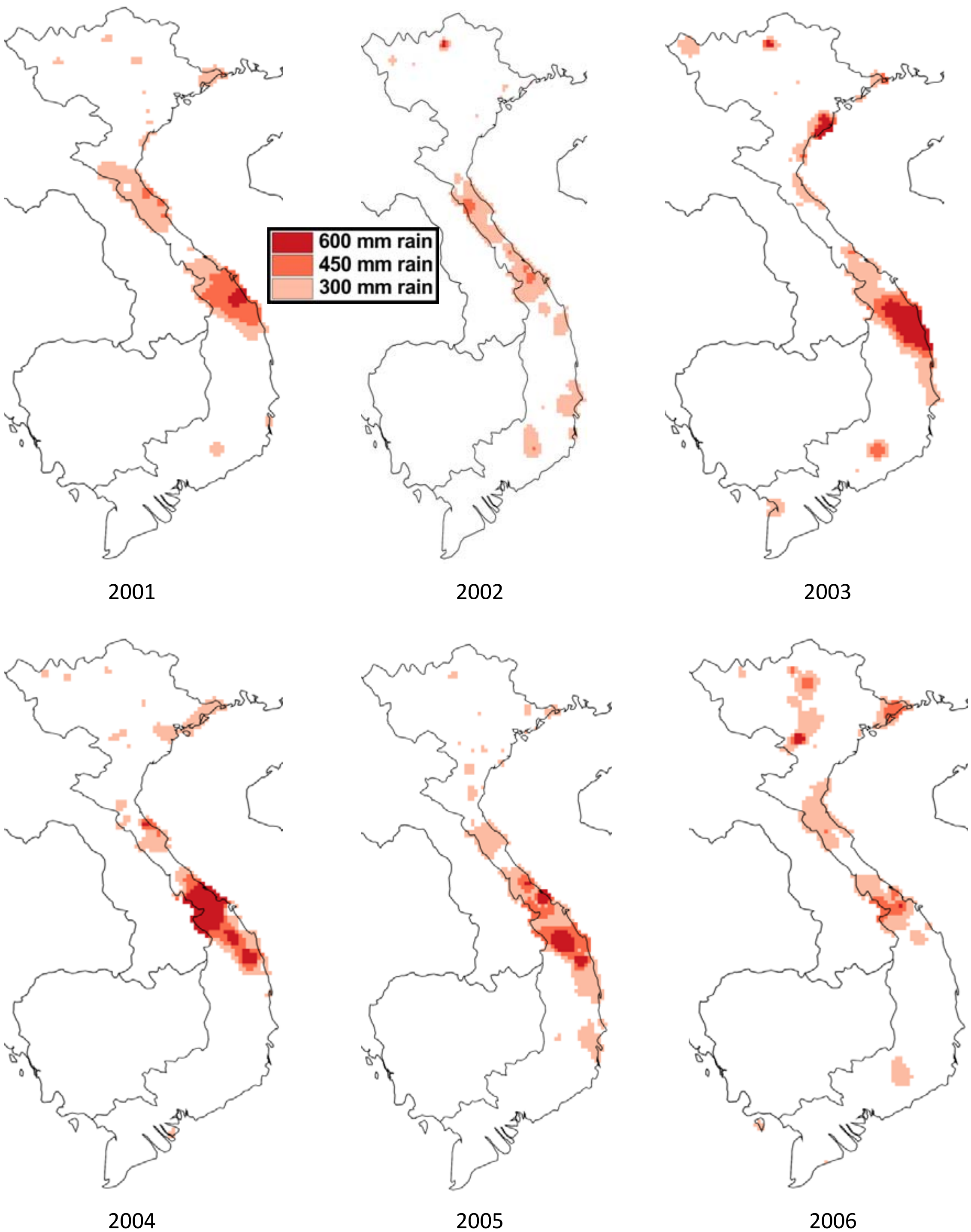
Source: Authors' calculations.

Figure 3. Proportion of years with 20 percent shortfall in median annual rainfall



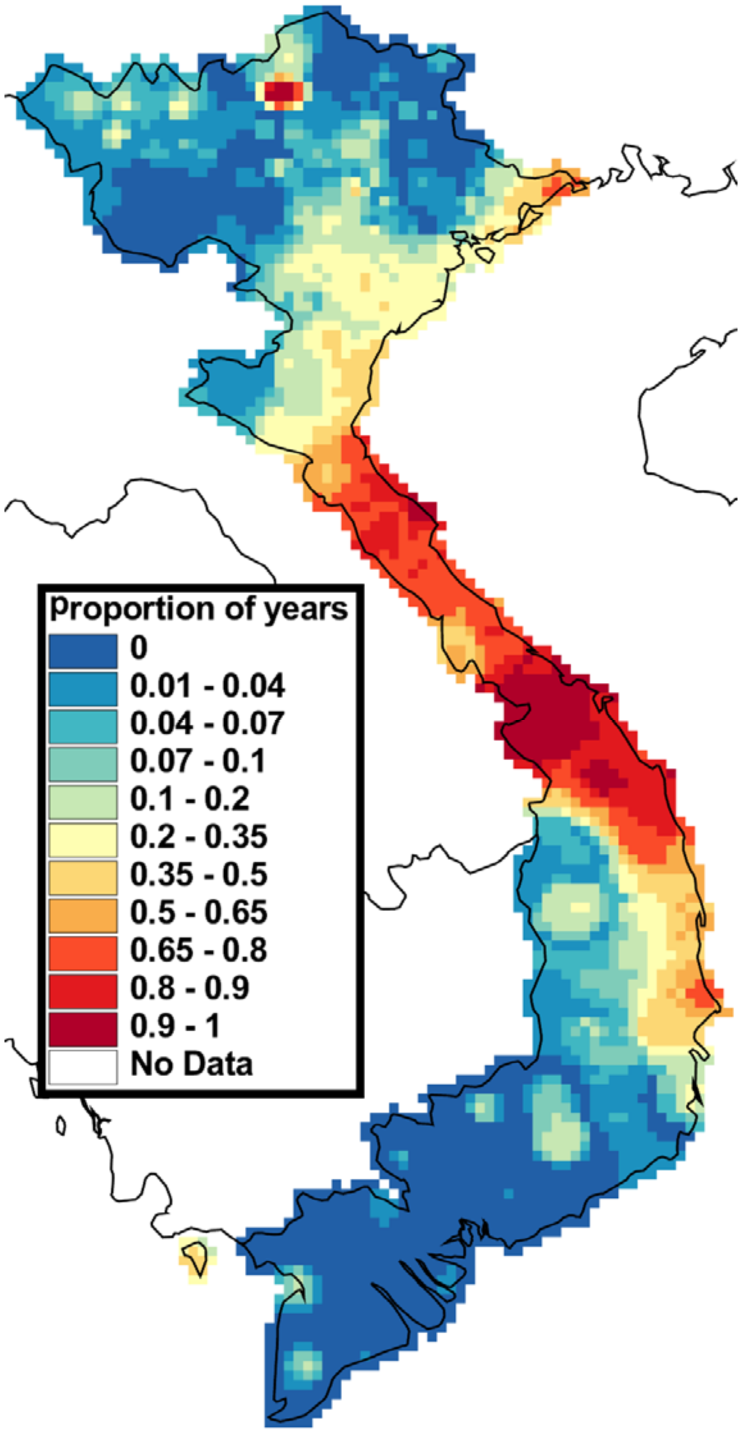
Source: Authors' calculations.

Figure 4: Localized flooding for each year 2001 to 2006.



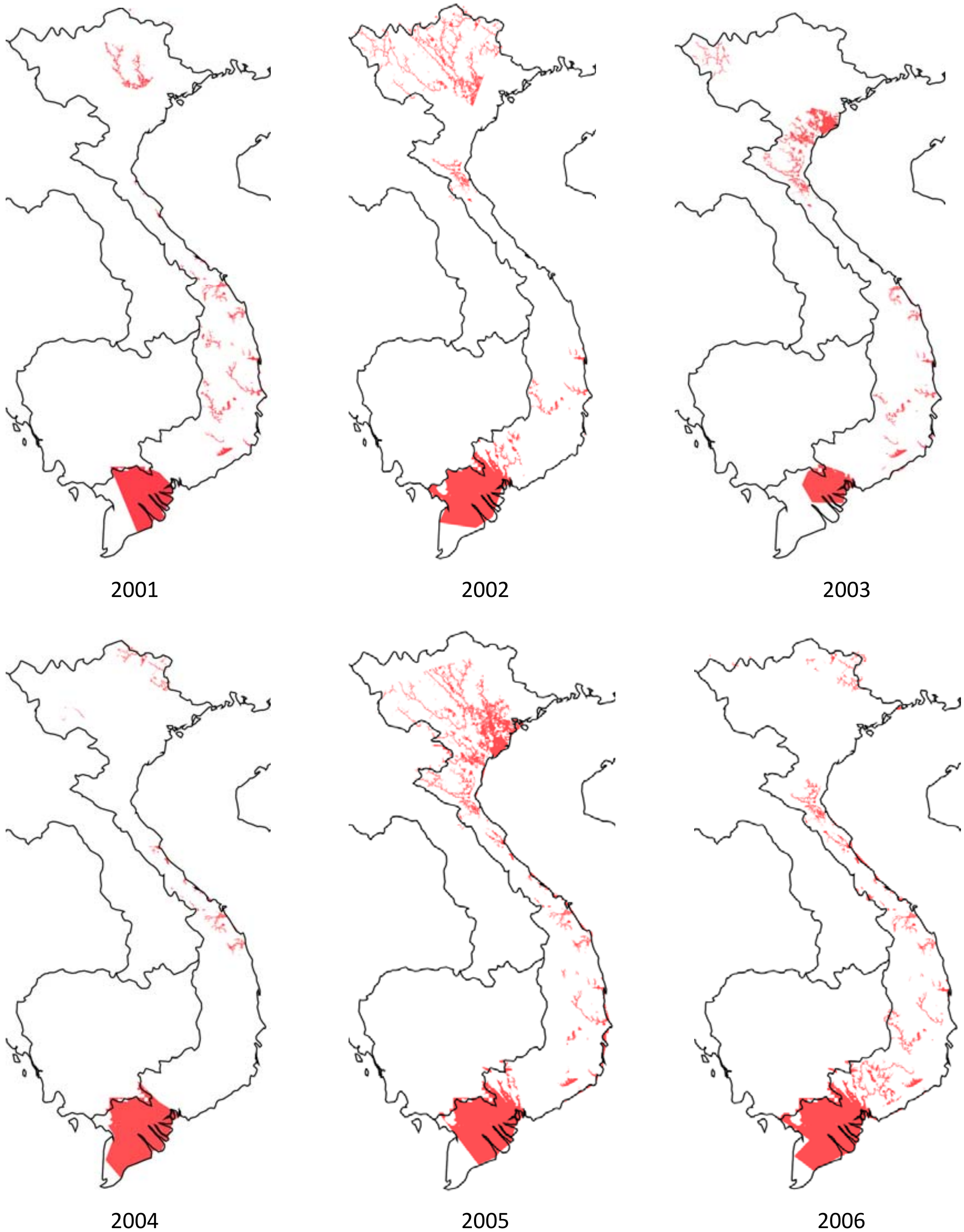
Source: Authors' calculations.

Figure 5: Proportion of years in which 300 millimeters of rain fell in a consecutive 5-day period



Source: Authors' calculations.

Figure 6: Riverine and coastal flooding for each year 2001 to 2006.



Source: Dartmouth Flood Observatory (2008) and authors’ calculations using Hydrosheds and GLOBE.

Figure 7: Proportion of riverine and coastal flooding 1985-2007.

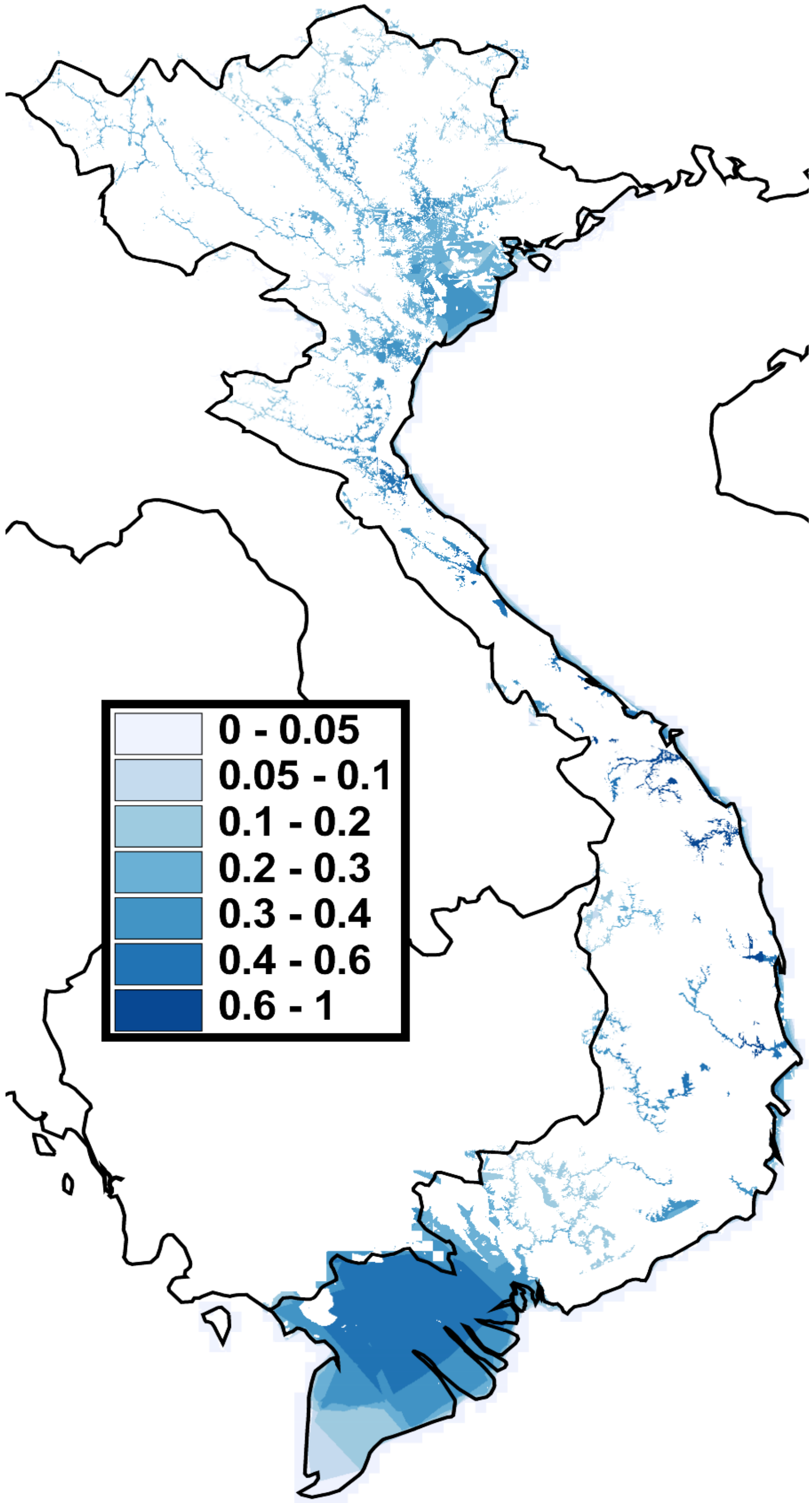
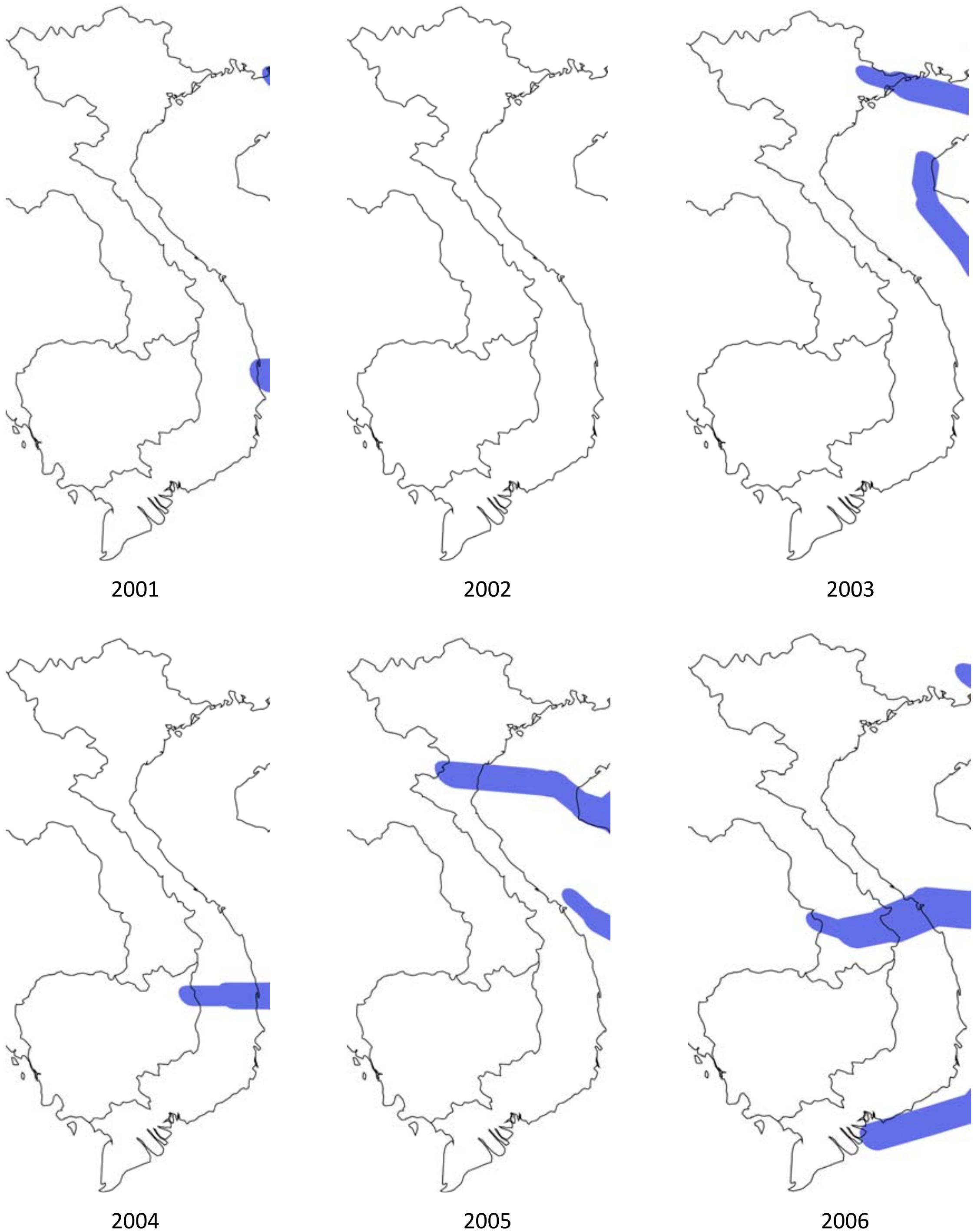
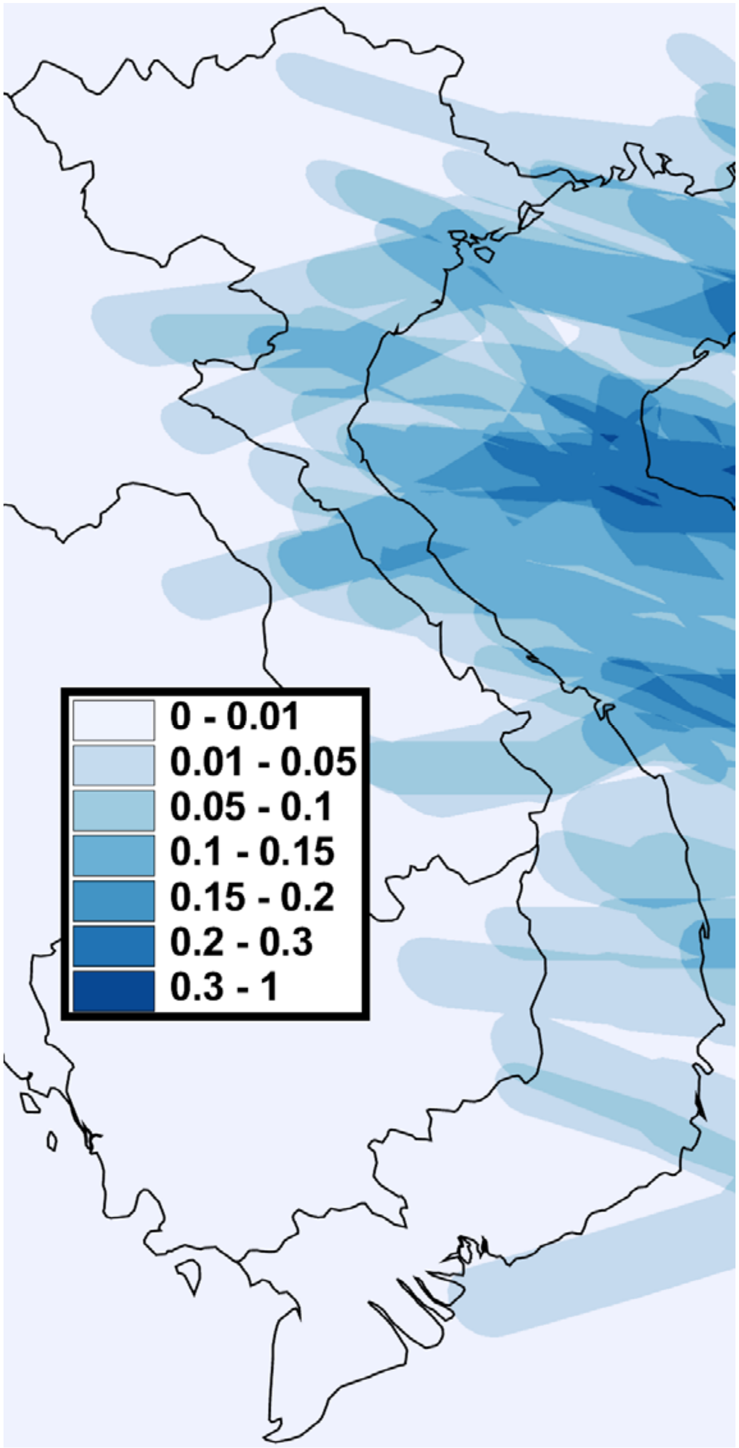


Figure 8: Hurricane force winds associated with tropical cyclones for 2001 to 2006.



Source: UNEP / GRID (2007) and author's calculations.

Figure 9: Proportion of years with hurricane force winds



Source: Authors' calculations, based on GNV199 (UNEP/GRID-Europe, 2007a).

Table 1: Extreme weather events can have substantial negative effects on household welfare, immediately and through adaptation over time, with adaptation and disaster relief often mitigating the immediate losses

Dependent variable: log expenditure/capita (excl. health expenditure)	OLS with Hubert-White heteroskedasticity and cluster design correction			ML corrected for spatial correlation, cluster design and heteroskedasticity
	(1)	(2)	(3)	(4)
	parameter/ t-value	parameter/ t-value	parameter/ t-value	parameter/ t-value
Extreme weather event in community				
Droughts				
Drought this year	0.0309***	0.0016	-0.0671	0.0245
	2.92	0.06	-1.04	0.58
Drought this year*drought frequency		0.3023	0.2918	0.0704
		1.48	1.39	0.46
Drought this year*ln(hours) from 500k city			0.0177	-0.0006
			1.23	-0.06
Drought last year	0.0118	0.004	0.1159	-0.0008
	0.44	0.06	0.45	-0.01
Drought last year*drought frequency		0.1253	0.0179	-0.1257
		0.35	0.05	-0.45
Drought last year*ln(hours) from 500k city			-0.0212	0.0111
			-0.39	0.31
Drought frequency (proportion)		-0.5241***	-2.5466***	-1.2609***
		-4.74	-5.54	-4.25
Drought frequency*ln(hours) from 500k city			0.5486***	0.2845***

			4.54	3.72
Excess rain				
Excess rain this year	0.0529***	-0.0658***	-0.1552***	-0.0768**
	4.14	-2.76	I. -2.92	II. -2.21
Excess rain this year*Excess rain frequency		0.1998***	0.0798	0.0685*
		4.24	1.28	1.90
Excess rain this year*ln(hours) from 500k city			0.0377**	0.0159
			2.2	1.49
Excess rain last year	0.0521***	0.0836***	0.1657**	0.1337***
	3.58	2.88	2.56	4.14
Excess rain last year*Excess rain frequency		-0.1104**	-0.1451**	-0.0852**
		-2.09	-2.26	-2.17
Excess rain last year*ln(hours) from 500k city			-0.0166	-0.0182*
			-0.9	-1.95
Excess rain frequency (proportion)		0.0980**	-0.3440*	-0.2828**
		1.97	-1.87	-2.26
Excess rain frequency*ln(hours) from 500k city			0.0894**	0.0798**
			2.11	2.77
Riverine flood				
Riverine flood this year	0.0649***	0.0133	-0.0536	-0.0575*
	4.4	0.37	-1.05	-1.87
Riverine flood this year*Riverine flood frequency		0.1418	0.1299	0.1440**
		1.29	1.22	2.20

Riverine flood this year*ln(hours) from 500k city			0.0129	0.0091
			1.02	1.17
Riverine flood last year	-0.0615***	-0.0132	-0.1961***	-0.1723***
	-5.44	-0.38	-4.22	-5.417
Riverine flood last year*Riverine flood frequency		-0.1263	-0.0521	-0.0051
		-1.22	-0.48	-0.07
Riverine flood last year*ln(hours) from 500k city			0.0488***	0.3397***
			3.71	3.66
Riverine flood frequency (proportion)		-0.032	0.5082***	0.0407***
		-0.65	3.39	4.87
Riverine flood frequency*ln(hours) from 500k city			-0.1513***	-0.1041***
			-3.88	-4.24
Hurricane force wind				
Hurricane force wind this year	0.0185	-0.0726	-0.4159	-0.7309***
	0.79	-1.16	-1.14	-2.93
Hurricane force wind this year*Hurricane force wind frequency		1.3281**	0.0739	-0.9634
		2.08	0.09	-1.41
Hurricane force wind this year*ln(hours) from 500k city			0.0886	0.1737***
			1.07	2.99
Hurricane force wind last year	0.0384	0.1967*	0.0658	-0.1642
	1.29	1.95	0.29	-0.96
Hurricane force wind last year*Hurricane force wind frequency		-1.1792	-1.197	-1.4028**
		-1.23	-1.28	-2.06
Hurricane force wind last year*ln(hours) from 500k city			0.0281	0.0762**

			0.54	1.97
Hurricane force wind frequency (proportion)		-0.5151***	-2.0504***	-2.1608***
		-3.42	-4.83	-7.45
Hurricane force wind frequency*ln(hours) from 500k city			0.4566***	0.4584***
			3.68	5.79
Household characteristics				
log of household size	-0.2419***	-0.2447***	-0.2474***	-0.2832***
	-36.06	-36.83	-37.38	-56.634
dependency ratio	-0.0046***	-0.0046***	-0.0046***	-0.0047***
	-28.82	-28.96	-28.92	-36.03
1 if ethnic minority; 0 otherwise	-0.2388***	-0.2411***	-0.2396***	-0.2422***
	-16.32	-16.49	-16.66	-29.05
1 if household head is female	0.0123*	0.0104*	0.0081	0.0005
	1.93	1.65	1.3	0.10
log of age of household head	0.1233***	0.1236***	0.1217***	0.1317***
	13.44	13.54	13.47	18.71
education household head = 1 if				
primary school	0.1556***	0.1564***	0.1553***	0.14073***
	22.64	22.91	22.96	26.99
Lower secondary school	0.2618***	0.2659***	0.2659***	0.2524***
	33.02	33.83	34.16	44.32
Higher secondary school	0.4159***	0.4187***	0.4186***	0.39063***
	37.96	38.45	39	47.55

Short-term technical worker	0.4881***	0.4993***	0.5066***	0.47005***
	32.19	33.25	33.84	37.51
Long-term technical worker	0.5566***	0.5626***	0.5668***	0.5312***
	38.19	38.83	39.74	44.43
Professional secondary school	0.5787***	0.5832***	0.5833***	0.55974***
	37.36	37.69	37.8	42.96
College diploma and above	0.8133***	0.8130***	0.8099***	0.76219***
	51.35	52.7	54.59	65.25
Days ill in bed, senior household members	0.0001	0.0001	0.0001	0.0000
	0.71	0.67	0.6	0.47
Days ill in bed, adult household members	-0.0002	-0.0002	-0.0002	-0.0002***
	-1.42	-1.45	-1.57	-2.07
Days ill in bed, children	0.0001	0.0002	0.0002	0.0002
	0.74	0.84	0.84	0.94
Own a house (1=yes; 0=no)	0.1393***	0.1415***	0.1493***	0.1592***
	9.01	9.28	10.31	15.40
Own land (1=yes;0=no)	-0.7036***	-0.6848***	-0.6848***	-0.7334***
	-21.83	-21.67	-21.77	-37.63
Areas of land owned (squared metres)	0.0782***	0.0763***	0.0769***	0.0883***
	19.81	19.68	19.85	38.29
Community characteristics				
1 if sanitary drinking water in enumeration area	-0.0704	-0.0754	-0.0694	-0.0723*
	-1.5	-1.54	-1.52	-1.74
1 if sanitary living water in enumeration area	0.0853**	0.0881*	0.0854**	0.1014***

	1.97	1.92	2.03	2.51
1 if electricity in enumeration area	0.0047	0.0145	0.0057	0.0018
	0.15	0.46	0.18	0.12
1 if sanitary latrine in enumeration area	0.1062***	0.1087***	0.1124***	0.1002***
	7.33	7.51	7.79	12.88
1 if living on primary or secondary road	0.1199**	0.1011**	0.0856*	0.1080***
	2.43	2.07	1.79	4.26
Log of distance (km) to closest primary or secondary road	0.0234***	0.0210***	0.0182***	0.0194***
	3.45	3.13	2.77	5.53
Log (1+ elevation in meters)	0.0130**	0.0066	0.0066	0.0008
	2.15	1.04	1.05	0.22
Log (1+diff bw highest & lowest elevation in 1 km^2)	-0.0072	-0.0089	-0.0096	-0.0172***
	-1.05	-1.33	-1.46	-4.62
Log (1+tenths hours to urban area of > 25,000 people)	-0.0353***	-0.0366***	-0.0404***	-0.0530***
	-3.43	-3.5	-3.85	-8.10
Log (1+tenths of hours to urban area of > 100,000 people)	-0.0565***	-0.0555***	-0.0531***	-0.0426***
	-5.39	-5.23	-4.94	-6.03
Log (1+tenths of hours (6 minute periods) to urban area of > 500,000 people)	-0.0958***	-0.0947***	-0.1442***	-0.1190***
	-9.85	-9.57	-9.81	-11.73
Regional characteristics				
1 if urban; 0 otherwise	0.3176***	0.3128***	0.3045***	0.27923***
	21.81	21.79	21.22	34.94
Region 2: Northeast	0.0824***	0.0819***	0.0628***	0.0860***

	4.14	4.01	3.03	5.25
Region 3: Northwest	0.044	0.0505	0.0436	0.0335
	1.28	1.51	1.35	1.31
Region 4: Northcentral Coast	-0.0347	-0.0254	-0.0727***	-0.0504**
	-1.56	-1.04	-2.89	-2.41
Region 5: Southcentral Coast	0.2475***	0.2438***	0.1464***	0.1409***
	8.97	8.36	4.32	5.55
Region 6: Central Highlands	0.0664**	0.0900***	0.0411	0.0687***
	2.08	2.8	1.28	2.75
Region 7: Southeast	0.2904***	0.2881***	0.2367***	0.2347***
	15.97	13.07	9.76	12.07
Region 8: Mekong Delta	0.2757***	0.2701***	0.2518***	0.2157***
	11.24	8.42	7.8	9.86
1 if year 2004; 0 otherwise	0.3368***	0.3367***	0.3385***	0.33537***
	36.4	35.88	35.18	44.92
1 if year 2006; 0 otherwise	0.6360***	0.6387***	0.6458***	0.64451***
	69.34	67.54	67.28	88.39
Constant	7.5505***	7.6402***	7.8854***	7.0465***
	95.01	94.78	86.6	67.38
r2/ln L	0.57	0.57	0.58	-23,761.1
F	481.45	404.4	359.8	
N	46985	46985	46985	47,167

Pooled VHLSS data from 2002, 2004 and 2006. Drought if 20% below annual median rainfall; excess rainfall if > 300 mm in 5 consecutive days at least once in a year; flooding recorded in Darthmouth Flood Observatory and within 2 m elevation difference from river or coast; hurricane force winds if wind 65 knots (118 km/hour) or more.

ln(hours) from 500k city are in effect the ln(1+ tenths of hours) from 500k city with tenths of hours being 6 minute periods

Table 2: Extreme weather events can have substantial negative effects on household welfare, immediately and through adaptation over time, with adaptation and disaster relief often mitigating the immediate losses

Dependent variable	Log exp/capita (excl. health expenditure)	Log (asset and consumer durable value)	Disaster relief	Domestic remittances	Remittances from outside VN	Herfindahl index
	ML	OLS		Tobit		OLS
	(1)	(2)	(3)	(4)	(5)	(6)
	parameter/ t-value	parameter/ t-value	parameter/ t-value	parameter/ t-value	parameter/ t-value	parameter/ t-value
Extreme weather event in community						
Droughts						
Drought this year	0.0245	0.193	-667	423	-13387*	-0.0232
	0.58	0.95	-0.5	0.91	-1.91	-0.92
Drought this year*drought frequency	0.0704	0.9981				0.029
	0.46	1.22				0.36
Drought this year*ln(hours) from 500k city	-0.0006	-0.0923*	549	-128	4192**	0.0058
	-0.06	-1.95	1.56	-1.07	2.28	1.03
Drought last year	-0.0008	-1.2525*	-288	-2208	17699	0.0538
	-0.01	-1.68	-0.05	-1.49E+00	0.75	0.67
Drought last year*drought frequency	-0.1257	-1.0411				-0.1084
	-0.45	-0.85				-0.94
Drought last year*ln(hours) from 500k city	0.0111	0.3263**	-388	313	-4247	-0.0053
	0.31	2.24	-0.28	0.87	-0.72	-0.3
Drought frequency (proportion)	-1.2609***	-3.4800**	11703	10822***	64532	-0.3115**
	-4.25	-2.26	1.11	2.98	1.18	-2.15
Drought frequency*ln(hours) from 500k city	0.2845***	1.0100**	-3830	-2761***	-19709	0.0738*
	3.72	2.36	-1.43	-2.93	-1.35	1.96
Excess rain						

Dependent variable	Log exp/capita (excl. health expenditure)	Log (asset and consumer durable value)	Disaster relief	Domestic remittances	Remittances from outside VN	Herfindahl index
	ML	OLS		Tobit		OLS
	(1)	(2)	(3)	(4)	(5)	(6)
	parameter/ t-value	parameter/ t-value	parameter/ t-value	parameter/ t-value	parameter/ t-value	parameter/ t-value
Excess rain this year	-0.0768**	-0.3798**	-8908***	707	12524**	-0.0214
	-2.21	-2.51	-2.92	1.52	2.07E+00	-1.34
Excess rain this year*Excess rain frequency	0.0685*	-0.1213				-0.0265
	1.90	-0.51				-1.34
Excess rain this year*ln(hours) from 500k city	0.0159	0.1455***	2280***	-277**	-1759	0.0101*
	1.49	2.96	3.17	-2.34	-1.14	1.95
Excess rain last year	0.1337***	0.3661**	2005	1201**	-13616**	-0.016
	4.14	2.51	1.31	1.99	-2.25	-1.01
Excess rain last year*Excess rain frequency	-0.0852**	-0.5361**				-0.0191
	-2.17	-2.39				-0.86
Excess rain last year*ln(hours) from 500k city	-0.0182*	-0.0327	-310	-303**	3492**	0.0068
	-1.95	-0.74	-0.84	-2.05	2.3	1.47
Excess rain frequency (proportion)	-0.2828**	-0.8208	14364**	1237	-54117**	0.057
	-2.26	-1.49	2.52	0.85	-2.41	0.91
Excess rain frequency*ln(hours) from 500k city	0.0798**	0.1031	-3694***	-129	12517**	-0.0151
	2.77	0.73	-2.79	-0.39	2.53	-1.05
Riverine flood						
Riverine flood this year	-0.0575*	0.3427*	-1729	-826*	-6324	0.0267
	-1.87	1.93	-1.21	-1.87	-1.48	1.58
Riverine flood this year*Riverine flood frequency	0.1440**	-0.1806				-0.0531
	2.20	-0.48				-1.32

Dependent variable	Log exp/capita (excl. health expenditure)	Log (asset and consumer durable value)	Disaster relief	Domestic remittances	Remittances from outside VN	Herfindahl index
	ML	OLS		Tobit		OLS
	(1)	(2)	(3)	(4)	(5)	(6)
	parameter/ t-value	parameter/ t-value	parameter/ t-value	parameter/ t-value	parameter/ t-value	parameter/ t-value
Riverine flood this year*ln(hours) from 500k city	0.0091	-0.0955**	538	259**	1857	-0.006
	1.17	-2.24	1.43	2.14	1.41E+00	-1.4
Riverine flood last year	-0.1723***	-0.8076***	-2582**	-331	-2185	-0.0546***
	-5.417	-5.42	-2.04	-0.74	-0.42	-3.02
Riverine flood last year*Riverine flood frequency	-0.0051	1.2278***				-0.0018
	-0.07	2.91				-0.04
Riverine flood last year*ln(hours) from 500k city	0.3397***	0.1197***	612*	74	1222	0.0134***
	3.66	2.99	1.75	5.60E-01	7.90E-01	2.96
Riverine flood frequency (proportion)	0.0407***	0.6768	7506*	1177	11479	0.0434
	4.87	1.58	1.7	0.82	0.64	0.86
Riverine flood frequency*ln(hours) from 500k city	-0.1041***	-0.3161**	-1828*	-212	-4749	-0.0088
	-4.24	-2.49	-1.66	-0.56	-0.99	-0.66
Hurricane force wind						
Hurricane force wind this year	-0.7309***	0.0771	-40831	-2183	-22448	-0.0999
	-2.93	0.08	-1.32	-1.17	-0.58	-0.96
Hurricane force wind this year*Hurricane force wind frequency	-0.9634	1.1605				-0.2275
	-1.41	0.41				-0.71
Hurricane force wind this year*ln(hours) from 500k city	0.1737***	-0.0017	8208	626	3153	0.0188
	2.99	-0.01	1.33	1.54	0.39	0.75
Hurricane force wind last year	-0.1642	-1.7442***	-4902	-963	-79326*	0.0122

Dependent variable	Log exp/capita (excl. health expenditure)	Log (asset and consumer durable value)	Disaster relief	Domestic remittances	Remittances from outside VN	Herfindahl index
	ML	OLS		Tobit		OLS
	(1)	(2)	(3)	(4)	(5)	(6)
	parameter/ t-value	parameter/ t-value	parameter/ t-value	parameter/ t-value	parameter/ t-value	parameter/ t-value
	-0.96	-2.86	-0.76	-0.45	-1.7	0.19
Hurricane force wind last year*Hurricane force wind frequency	-1.4028**	-3.0042				-0.4922*
	-2.06	-1.32				-1.8
Hurricane force wind last year*ln(hours) from 500k city	0.0762**	0.4991***	1038	248	19613*	0.0105
	1.97	3.77	0.72	0.49	1.85E+00	0.74
Hurricane force wind frequency (proportion)	-2.1608***	-1.3598	-5555	-834	-9578	0.0226
	-7.45	-1	-0.46	-0.24	-0.22	0.18
Hurricane force wind frequency*ln(hours) from 500k city	0.4584***	-0.0417	1891	400	-8326	-0.0282
	5.79	-0.09	0.6	0.41	-0.65	-0.76
Household characteristics						
log of household size	-0.2832***	0.9004***	268**	-380***	1996**	-0.0772***
	-56.634	36.13	2.1	-6.2	2.01	-29.53
dependency ratio	-0.0047***	-0.0073***	25***	6***	49*	0.0010***
	-36.03	-14.26	4.07	3.27	1.78	15.03
1 if ethnic minority; 0 otherwise	-0.2422***	-0.9442***	482	-371***	3368	-0.0237***
	-29.05	-14.54	1.54	-3.11	1.49	-4.62
1 if household head is female	0.0005	-0.0971***	75	235***	4958***	-0.0037
	0.10	-4.56	0.53	3.6	4.5	-1.48
log of age of household head	0.1317***	0.1358***	269	1502***	11890***	-0.0019
	18.71	4.02	1.51	15.21	6	-0.49
education household head = 1 if						

Dependent variable	Log exp/capita (excl. health expenditure)	Log (asset and consumer durable value)	Disaster relief	Domestic remittances	Remittances from outside VN	Herfindahl index
	ML	OLS		Tobit		OLS
	(1)	(2)	(3)	(4)	(5)	(6)
	parameter/ t-value	parameter/ t-value	parameter/ t-value	parameter/ t-value	parameter/ t-value	parameter/ t-value
primary school	0.14073***	0.4720***	-68	130**	2851**	-0.0044
	26.99	17.65	-0.47	1.97	2.16	-1.55
Lower secondary school	0.2524***	0.7603***	13	106	5739***	-0.0112***
	44.32	28.11	0.07	1.5	3.78	-3.55
Higher secondary school	0.39063***	1.0970***	-469*	261**	11165***	-0.0018
	47.55	32.37	-1.96	1.99	5.68	-0.42
Short-term technical worker	0.47005***	1.2881***	-528	340**	10008***	0.0191***
	37.51	26.95	-1.48	2	3.66	2.83
Long-term technical worker	0.5312***	1.3951***	-359	635***	5688**	0.0218***
	44.43	31.19	-1.14	3.7	2.08	3.5
Professional secondary school	0.55974***	1.3057***	-1704***	345*	3299	0.0360***
	42.96	30.58	-3.06	1.79	1.14	5.56
College diploma and above	0.76219***	1.7775***	-654	1177***	378	0.0488***
	65.25	43.09	-1.44	5.19	0.16	7.32
Days ill in bed, senior household members	0.0000	0	2	3***	13	0
	0.47	0.09	0.77	2.86	0.89	0.76
Days ill in bed, adult household members	-0.0002***	-0.0017***	11***	3**	25*	0
	-2.07	-3.9	3.72	1.97	1.68	0.92
Days ill in bed, children	0.0002	-0.0004	7	3	-8	-0.0001
	0.94		1.49	1.29	-0.25	-0.91
Own a house (1=yes; 0=no)	0.1592***	0.8281***	-36	157	3892**	-0.0132**
	15.40	13.75	-0.13	0.79	2	-2.25
Own land (1=yes;0=no)	-0.7334***	-2.5031***	746	-306	-16968***	-0.1328***

Dependent variable	Log exp/capita (excl. health expenditure)	Log (asset and consumer durable value)	Disaster relief	Domestic remittances	Remittances from outside VN	Herfindahl index
	ML	OLS		Tobit		OLS
	(1)	(2)	(3)	(4)	(5)	(6)
	parameter/ t-value	parameter/ t-value	parameter/ t-value	parameter/ t-value	parameter/ t-value	parameter/ t-value
	-37.63	-23.52	1.26	-1.33	-3.51	-10.36
Areas of land owned (squared metres)	0.0883***	0.3802***	-138*	40	1265**	-0.0038**
	38.29	28.21	-1.93	1.4	2.2	-2.38
Community characteristics						
1 if sanitary drinking water in enumeration area	-0.0723*	0.1658	-949**	-124	-2687	0.0011
	-1.74	0.47	-2.09	-0.84	-1.02	0.04
1 if sanitary living water in enumeration area	0.1014***	-0.1143	18	96	8013***	0.014
	2.51	-0.34	0.04	0.6	2.67	0.58
1 if electricity in enumeration area	0.0018	0.18	76	333***	2023	-0.0324**
	0.12	0.96	0.31	3.36	0.87	-2.09
1 if sanitary latrine in enumeration area	0.1002***	0.4157***	-179	403***	13758***	0.0176***
	12.88	6.65	-1.1	6.47	9.02	3.22
1 if living on primary or secondary road	0.1080***	-0.2622	1127	216	-4525	-0.0018
	4.26	-1.54	1.13	0.57	-0.79	-0.11
Log of distance (km) to closest primary or secondary road	0.0194***	-0.0373	117	56	-432	-0.0012
	5.53	-1.55	0.88	1.11	-0.53	-0.52
Log (1+ elevation in meters)	0.0008	0.003	94	61	2879**	-0.0035
	0.22	0.1	0.44	0.69	2.21	-1.03
Log (1+diff bw highest & lowest elevation in 1 km^2)	-0.0172***	-0.0773**	-359	-161*	-4553***	-0.0004
	-4.62	-2.51	-1.56	-1.84	-3.98	-0.11
Log (1+tenths hours to urban area of	-0.0530***	-0.1523***	626*	-199*	-1339	0

Dependent variable	Log exp/capita (excl. health expenditure)	Log (asset and consumer durable value)	Disaster relief	Domestic remittances	Remittances from outside VN	Herfindahl index
	ML	OLS		Tobit		OLS
	(1)	(2)	(3)	(4)	(5)	(6)
	parameter/ t-value	parameter/ t-value	parameter/ t-value	parameter/ t-value	parameter/ t-value	parameter/ t-value
> 25,000 people)						
	-8.10	-3.58	1.72	-1.67	-0.83	-0.01
Log (1+tenths of hours to urban area of > 100,000 people)	-0.0426***	0.0482**	46	43	-1286	0.0023
	-6.03	2.22	0.35	0.91	-1.45	1.1
Log (1+tenths of hours to urban area of > 500,000 people)	-0.1190***	-0.0751***	276*	-62	-152	-0.0022
	-11.73	-3.28	1.74	-1.15	-0.15	-0.99
Regional characteristics						
1 if urban; 0 otherwise	0.27923***	0.4571***	-469	30	2260	0.0247***
	34.94	10.56	-1.52	0.25	1.44	5.48
Region 2: Northeast	0.0860***	0.1445**	1004*	304*	1642	-0.0226***
	5.25	2.46	1.67	1.93	6.20E-01	-3.49
Region 3: Northwest	0.0335	0.0545	1637**	-454	9462*	0.017
	1.31	0.43	2.14	-1.29	1.87	1.45
Region 4: Northcentral Coast	-0.0504**	0.0366	1516**	613***	7550**	-0.0072
	-2.41	0.48	2.32	3.51	2.46	-0.91
Region 5: Southcentral Coast	0.1409***	0.2884***	5111***	515**	8506**	0.0254**
	5.55	2.8	4.44	2.15	2.08	2.49
Region 6: Central Highlands	0.0687***	0.1144	1936**	811***	5428	0.0605***
	2.75	0.87	2.32	3.24	1.18	5.24
Region 7: Southeast	0.2347***	0.2871***	3449***	835***	12333***	0.0825***
	12.07	3.88	4.2	4.32	3.87	10.37
Region 8: Mekong Delta	0.2157***	0.2418**	2840***	686***	13412***	0.0927***
	9.86	2.29	3.6	2.91	3.64	8.84

Dependent variable	Log exp/capita (excl. health expenditure)	Log (asset and consumer durable value)	Disaster relief	Domestic remittances	Remittances from outside VN	Herfindahl index
	ML	OLS		Tobit		OLS
	(1)	(2)	(3)	(4)	(5)	(6)
	parameter/ t-value	parameter/ t-value	parameter/ t-value	parameter/ t-value	parameter/ t-value	parameter/ t-value
1 if year 2004; 0 otherwise	0.33537***	0.7683***	-5885***	729***	-304	-0.0395***
	44.92	23.52	-5.23	6.33	-0.2	-10.53
1 if year 2006; 0 otherwise	0.64451***	1.0031***	-4341***	1050***	249	-0.0246***
	88.39	30.59	-5.08	9.79	0.16	-6.59
Constant	7.0465***	5.7400***	-12589***	-5697***	-121334***	0.7821***
	67.38	14.06	-4.1	-8.86	-8.12	22.73
r2/ln L		0.3				0.29
F		135.18	0.77	16.14	3.56	127.76
N	47,167	46985	46985	46985	46985	46916

Pooled VHLSS data from 2002, 2004 and 2006. ML corrected for spatial correlation, cluster design and heteroskedasticity. OLS and Tobit estimators corrected for cluster design and heteroskedasiticy using Hubert-White correction. Drought if 20% below annual median rainfall; excess rainfall if > 300 mm in 5 consecutive days at least once in a year; flooding recorded in Darthmouth Flood Observatory and within 2 m elevation difference from river or coast; hurricane force winds if wind 65 knots (118 km/hour) or more.

ln(hours) from 500k city are in effect the ln(1+ tenths of hours) from 500k city with tenths of hours being 6 minute periods

Table A1: Inverse elevation difference weighted rainfall index most important in predicting monthly rainfall in wettest months (April-November), while inverse distance squared weighted rainfall index also important for predicting rain during drier months (December-March)

Dependent variable = log (monthly rainfall)				
month	constant	inverse distance squared weighted rainfall index	inverse elevation difference weighted rainfall index	mean rainfall (mm)
1	-0.19	0.64	0.34	24.7
2	-0.27	0.49	0.52	27.5
3	-0.56	0.34	0.75	41.3
4	-0.95	0.06	1.11	78.1
5	-0.72	0.02	1.10	220.8
6	-1.05	0.07	1.10	232.1
7	-1.16	0.08	1.11	277.1
8	-0.95	0.07	1.09	314.7
9	-0.20	0.05	0.97	242.2
10	-0.51	0.16	0.91	194.8
11	-0.30	0.32	0.69	117.2
12	-0.13	0.58	0.38	65.6

Notes: OLS estimated coefficients from regressing (log) monthly rainfall in 166 rainfall stations from across in Vietnam during 1980-2006 on the logs of their respective inverse distance squared weighted and inverse elevation difference weighted indices, monthly dummies and their interaction terms; R-squared=0.768; Mean rainfall reflects averages of rainfall stations taken over 2001-2006 R-squared: 0.768

Table A2: Temporal and cross disaster correlation of extreme weather events

		drought (20%<median)			flash flood (>300mm in 5 consec days)			river flood (DFO, <2m elevation diff)			hurricane		
		this year	last year	incidence	this year	last year	incidence	this year	last year	incidence	this year	last year	incidence
drought (20%<median)	this year	1											
	last year	-0.0079	1										
	incidence	0.242	0.1474	1									
flash flood (>300mm in 5 consec days)	this year	-0.1351	0.033	0.1219	1								
	last year	-0.0322	0.0249	0.2783	0.4409	1							
	incidence	-0.1247	0.102	0.3386	0.6106	0.7001	1						
river flood (DFO, <2m elevation diff)	this year	0.3488	0.0051	0.1178	-0.1609	-0.1628	-0.3001	1					
	last year	0.4008	-0.0288	0.1916	-0.0985	-0.0693	-0.1617	0.5465	1				
	incidence	0.3723	0.0045	0.2108	-0.1331	-0.1091	-0.1954	0.7497	0.7305	1			
hurricane	this year	0.0407	0.0439	0.0451	0.0044	0.1672	0.1503	-0.0377	-0.0142	-0.0321	1		
	last year	-0.044	-0.0149	0.1372	0.013	-0.0303	0.0954	-0.0377	0.0067	-0.0283	-0.0114	1	
	incidence	-0.161	0.0623	0.2017	0.2614	0.2953	0.5501	-0.3945	-0.1772	-0.1991	0.1151	0.1327	1

Table A3: Households further away from the metropolitan centers are more engaged in agriculture, have less assets and irrigated land, are less likely to receive remittances from abroad, but as likely or more likely to receive domestic remittances and disaster relief, albeit at much smaller amounts than those closer to the metropolitan centers

Distance from 500k city (hrs)	Ratio of household employees engaged in		asset holdings		support systems					
averages	wage earner	farmer	share of land irrigated	log(value of durable and fixed assets)	Share households receiving disaster relief	average disaster relief received[1)]	share households receiving domestic remittances	average domestic remittances received[1)]	share households with remittances from abroad	average remittances received from abroad[1)]
< 1 hour	0.51	0.19	0.91	9.73	0.05	2038	0.83	3513	0.13	19303
1-5 hours	0.28	0.53	0.87	9.14	0.08	1013	0.88	2073	0.05	14284
5-10 hours	0.25	0.59	0.72	9.08	0.09	1252	0.79	1741	0.05	16729
> 10 hours	0.30	0.50	0.72	9.05	0.12	634	0.85	1626	0.06	12475
Total	0.31	0.48	0.82	9.21	0.08	1096	0.85	2172	0.07	16017

1) average amounts among those who received disaster relief or remittances