The multifaceted relationship between environmental risks and poverty: new insights from Vietnam

Ulf Narloch[1] and Mook Bangalore[2,1]*

[1]The World Bank, Washington, DC, USA and [2]Department of Geography and Environment, Grantham Research Institute on Climate Change and the Environment, London School of Economics, London, UK
*Corresponding author. E-mail: M.Bangalore@lse.ac.uk

Abstract
Despite complex interlinkages, insights into the multifaceted relationship between environmental risks and poverty can be gained through an analysis of different risks across space, time and scale within a single context using consistent methods. Combining geo-spatial data on eight environmental risks and household survey data from 2010–2014 for the case study of Vietnam, this paper shows: (i) at the district level, the incidence of poverty is higher in high risk areas, (ii) at the household level, poorer households face higher environmental risks, (iii) for some risks the relationship with household-level consumption varies between rural and urban areas, and (iv) environmental risks explain consumption differences between households, but less so changes over time. While altogether these analyses cannot establish a causal relationship between environmental risks and poverty, they do indicate that Vietnam's poor are disproportionally exposed. Given growing pressures due to climate change, addressing such risks should be a focus of poverty reduction efforts.

1. Introduction

When devising poverty reduction strategies in the face of climate change, the role of environmental risks in the livelihoods of poor people needs to be understood. First, people struggling with multiple environmental risks generally have a lower ability to cope with other shocks and are thus more vulnerable to climate change impacts. Second, climate change will directly exacerbate weather-related environmental risks, such as rainfall and temperature variability and extremes and thereby increase this baseline vulnerability. Accordingly, poor people already exposed to high environmental risks could be most affected by climate change.

The interlinkages between poverty and environmental risks have been reviewed in earlier papers covering the extensive literature on this topic (Reardon and Vosti, 1995; Duraiappah, 1998; Scherr, 2000; Gray and Moseley, 2005; Barbier, 2010, 2012; Barrett *et al.*, 2011). Environmental risks are unevenly distributed across space – depending on geographic and climatic conditions, as well as socioeconomic factors that condition them. Poor people often live in remote and fragile areas, with high levels of environmental risks, where they overly depend on the use of ecosystems and natural resources, which can increase ecosystem fragility and environmental risks. This downward spiral could result in spatial poverty traps, where pockets of fragility, risks, marginalization and poverty persist (Carter *et al.*, 2007; Barbier, 2010; Barrett *et al.*, 2011). These poverty traps could be further exacerbated by climate change.

To guide policies to break out of these traps, there is a need for more in-depth, spatial analyses which try to disentangle the relationship between environmental risks and poverty (Barbier, 2012). While there is ample empirical work showing a positive relationship between environmental risks and poverty at the global and regional levels (e.g., Chomitz *et al.*, 2007; Barbier, 2010, 2015; Sloan and Sayer, 2015), the national and subnational levels (e.g., Dasgupta *et al.*, 2005; Bandyopadhyay *et al.*, 2011; Winsemius *et al.*, 2015) or in specific locations (Khan and Khan, 2009; Watmough *et al.*, 2016), all this work together points to a complex picture, where the relationship depends on the specific types of risks and locations of interest, as well as the channels through which they interact. New, high-resolution spatial data, for example from remote sensing, allows us to analyze the distribution of environmental risks and poverty across space in order to better understand the multifaceted nature of this relationship.

Vietnam provides an interesting case study for such an analysis. Despite a reduction of extreme poverty from around 60 per cent in 1990 to 13.5 per cent as of 2014 (World Bank Group, 2016),[1] pockets of poverty still exist today: 91 per cent of people in extreme poverty live in rural areas and belong to marginal groups, such as ethnic minorities, who have a poverty rate of about 58 per cent (Kozel, 2014). At the same time Vietnam is facing various environmental challenges. Land is increasingly degraded by human-induced factors (Vu *et al.*, 2014a, b). Although total tree cover has increased, certain areas suffer from high rates of forest loss and degradation (Pham *et al.*, 2012). Air pollution is an increasing concern (Luong *et al.*, 2017). And weather variability and extreme events, such as floods and droughts, severely affect livelihoods (Thomas *et al.*, 2010; Bui *et al.*, 2014; Arouri *et al.*, 2015; Narloch, 2016). An earlier spatial analysis at the provincial level in Vietnam, however, finds that the relationship between poverty and environmental risks is hard to generalize (Dasgupta *et al.*, 2005).

This paper revisits this relationship, taking advantage of more recent and higher-resolution data to examine four research questions: (RQ1) At the district level, is the incidence of poverty higher in high risk areas? (RQ2) At the household level, do poor households face higher environmental risks? (RQ3) Does the relationship between household-level consumption and environmental risks vary between rural and urban areas? (RQ4) Do environmental risks relate to consumption differences between households and consumption changes over time? On their own, many of these questions have been addressed in the existing literature, but they have hardly been brought together to

---

[1] This number is based on the national poverty line, which is at is US$3.49 per day in 2011 PPP terms. By the US$1.90 per day poverty line, the extreme poverty rate was 3% in 2014.

draw a comprehensive picture of the relationship between poverty and multiple environmental risks within a single country context using high-resolution data. We contribute to existing work by assessing how the relationship between poverty and multiple dimensions of environmental risk varies as a function of the channels through which poverty and risk interact, using a set of consistent data and methods while holding constant national context.

In this paper a number of recently-developed high-resolution datasets are used to separately assess eight environmental risks: (i) outdoor air pollution as a proxy for health risks through respiratory diseases (from Brauer *et al.*, 2015); (ii) tree cover loss as a proxy for the loss of forest resources and ecosystem functions (from Hansen *et al.*, 2013); (iii) land degradation as a proxy for productivity decline and agricultural production risks (from Vu *et al.*, 2014b); (iv) slope as a proxy for areas vulnerable to erosion and landslides (from World Soil Database); (v-vi) long-term rainfall and temperature variability as a proxy for the variation of weather conditions (from the Climate Research Unit (CRU)); (vii) flood hazards as a proxy for rainfall- and coastal-related extreme events (from Bangalore *et al.*, 2016); and (viii) drought hazards as a proxy for drought events (from Winsemius *et al.*, 2015).

These data are combined with national maps showing the incidence of poverty at the district level in 2010 (Lanjouw *et al.*, 2013). In addition, this study computes environmental risks at the commune level[2] to relate it to household information based on the latest Vietnam Household Living Standard Surveys (VHLSS) for 2010, 2012, and 2014 to examine whether environmental risks vary between households. Benefiting from the panel structure of these surveys, we also assess how environmental risks are related to consumption changes over time.

The remainder of this paper is structured as follows. Section 2 starts by deriving four research questions regarding the environmental risk and poverty linkages from existing literature. Section 3 describes the data used for the analysis of these research questions. The following four sections present the results. Section 4 shows the district-level overlay of environmental risks and poverty in 2010 (RQ1). Section 5 compares environmental risks at the commune level across household groups (RQ2). Building on these analyses, section 6 investigates differences in the relationship between household consumption levels and environmental risks between rural and urban areas (RQ3). Section 7 deepens these analyses by presenting results from various regression models explaining consumption differences between households and changes over time by environmental risks at the commune level (RQ4). Section 8 concludes.

2. Conceptual framework

What do we know about the association between environmental risks and poverty? Intuition suggests that the two are positively associated: the higher the level of environmental risk, the higher the incidence of poverty (conversely, the lower the level of consumption). While empirical work lends some support to this claim, the relationship is multifaceted. In this section, we examine dimensions over which poverty and environmental risks might vary: (1) across risk, space, time, and scale, (2) between rural and urban areas, and (3) depending on the channels that determine the relationship. While the framework presented below does not fully address all the different dimensions and causes that

---

[2]These are third-level administrative subdivisions, equivalent to a sub-district.

underpin this complex relationship and is not supposed to integrate the full set of frameworks existing in this field, it does serve to motivate the empirical approach taken in this paper, which is to examine the multifaceted relationship across many risks in the single context of Vietnam.

2.1 Differences across risk, space, time, and scale

The literature associated with the environmental Kuznets curve (Panayotou, 1997) argues that the relationship between environmental risks and incomes might be inversely U-shaped, with environmental degradation increasing with income levels up until a threshold is reached, after which degradation rates decrease. While consistent and rigorous evidence for this hypothesis has not been confirmed across a wide range of studies (for a review, see Stern, 2004), the framework highlights the fact that the relationship between environmental risks and poverty is not monotonic or straightforward.

Nevertheless, a range of studies in the literature point to a positive relationship between environmental risks and poverty. At the global level, various studies show that environmental risks are higher in poorer countries (Barbier, 2010, 2015; Barrios *et al.*, 2010; Sloan and Sayer, 2015). Studies at the sub-national level show that in some high-risk provinces and districts, the incidence of poverty is higher (Dasgupta *et al.*, 2005; Winsemius *et al.*, 2015; Watmough *et al.*, 2016). Similarly, at the household level, poorer households are found to have a higher exposure to some environmental risks than wealthier households (Ranger *et al.*, 2011; Akter and Mallick, 2013; Wodon *et al.*, 2014). Yet overall the findings are mixed and very context dependent.

First, the relationship depends on the specific risk being considered. For example, Hallegatte *et al.* (2016) find that within countries, poorer areas are also more exposed to higher temperatures and drought, but not to floods. In terms of air pollution, poor people tend to be more exposed to both ambient (outdoor) but also indoor air pollution. For outdoor air pollution, studies focused mostly in the developed world find that polluting industries (including coal plants) often locate in lower-income neighborhoods (Braubach and Fairburn, 2010). In terms of indoor air pollution, poorer households in developing countries remain highly reliant on firewood or biomass for cooking, with women and children living in severe poverty having the highest exposure levels (Gordon *et al.*, 2014). One recent study that has looked at different environmental risks in Lao PDR finds strong connections with poverty for indoor air pollution and water quality, weak connections for deforestation and soil erosion and no connection for outdoor air pollution (Pasanen *et al.*, 2017).

For some environmental risks, even a negative relationship could exist, resulting from economic development that has increased welfare levels but degraded ecosystems, such as agricultural intensification or land expansion into natural areas. For example, rural households in sub-Saharan Africa, many of whom are poor, often rely on charcoal production to support growing demand in urban areas. While this contributes to poverty reduction through income-generation opportunities, it can also undermine soil and ecosystem stability and thereby agricultural production (Zulu and Richardson, 2013). Generally, deforestation can deprive rural households of natural resources they depend on, while at the same time providing new income sources (Chomitz *et al.*, 2007; Laurance *et al.*, 2014). Where these contrasting effects coexist, it is possible that no significant relationship between degradation and poverty can be found.

More generally, within a country, the relationship between environmental risks and poverty is likely to change over time. For instance, Ebenstein *et al.* (2015) observe that

over the period of 1991–2002, China increased incomes and reduced poverty, as well as increasing air pollution. While high levels of air pollution increased mortality rates, economic growth and poverty reduction have also been associated with other health improvements that likely outweighed air pollution impacts. Also, where ecosystems have already been degraded substantially in the past, further degradation will be limited. Such change over time may explain why areas with low soil erosion rates tend to be poorer (Naipal *et al.*, 2015).

Generally, poverty and environmental risks are unevenly distributed across space so that the relationship also depends on the places considered. The spatial distribution of environmental risks and poverty varies greatly between countries, being shaped by a combination of agro-climatic and socio-economic conditions (Tucker *et al.*, 2015). Even in geographically similar countries, different patterns can be observed, as shown by Dasgupta *et al.* (2005): while in Lao PDR there is a spatial correlation between poverty and all environmental risks, in Cambodia, poverty is only positively related to household-level risk factors, such as indoor air pollution and lack of access to adequate water and sanitation. For Vietnam, the authors only find a positive relationship with fragile soils and indoor air pollution.

Moreover, the scale of the analysis matters too. For example, Winsemius *et al.* (2015) find mixed evidence for a higher exposure of poor people to climate-related risks, such as floods, when looking at poverty and risk levels at the district level. This finding could emerge because even within a district, poverty and risks may be very unevenly distributed, so more granular data at the local level from household surveys or case studies is needed. Indeed, looking at the same risk within a city – Mumbai, India – Ranger *et al.* (2011) find that poorer households in Mumbai are almost twice as exposed to floods.

However, analyses at higher resolution (e.g., household level) do not always show a positive association between environmental risks and poverty. Various studies show that there is no considerable difference between poor and wealthier households in their exposure to natural disaster risks (del Ninno, 2001; Carter *et al.*, 2007; Opondo, 2013). These findings may be explained by the scale of the risk (in some cases, everyone is exposed as in the case of drought), but highlight that the relationship between poverty and exposure to environmental risks is context specific and depends on the type of hazard, local geography, institutions and other mechanisms (Hallegatte *et al.*, 2016).

Thus overall the relationship between environmental risks and poverty remains an empirical question that depends on the specific risk types and locations of interest and the scale considered. Accordingly, it needs to be tested whether patterns at the provincial or district level hold at the household level. From this we derive our first and second research questions, (RQ1) and (RQ2), regarding the relationship between risks and poverty at different scales: (RQ1) Is the incidence of poverty (P) at the district level higher in high risk areas than low risk areas? And (RQ2), at the household level is the level of environmental risks (R) higher for poor than for non-poor households?

$$\text{District} - \text{level} : P_{\text{High Risk Areas}} > P_{\text{Low Risk Areas}} \tag{1}$$

$$\text{Household} - \text{level} : R_{\text{Poor}} > R_{\text{Non-Poor}} \tag{2}$$

2.2 Differences between rural and urban areas

While various studies address the relationship between environmental risks and poverty in rural or urban areas, so far not many studies have examined differences between

rural and urban spaces within the same country. Yet the extent of poverty, as well as the spatial distribution of poor people in the countryside, can differ substantially from cities, so the relationship between environmental risks and poverty could also vary.

First of all, rural and urban areas differ in wealth levels and thus the incidence of poverty. Rural areas have generally lower consumption levels and poverty continues to be mostly a rural problem. In 2012, 78 per cent of the global population in extreme poverty was living in rural areas (Olinto *et al.*, 2013). At the same time, more and more destitute people are moving into cities in search of new opportunities, so inequalities in urban areas may be increasing (Fox, 2014). In many countries, rural populations are concentrated in fragile areas with higher levels of environmental risks, including land degradation (Barbier, 2010) and terrain ruggedness (Nunn and Puga, 2012). While some hotspots where high risks and poverty coincide can be found, environmental risks could also be higher in wealthier areas (Pasanen *et al.*, 2017). Many case studies show how marginal people in rural areas face environmental risks: for example, precipitation variability in the Peruvian Andes (Sietz *et al.*, 2012), floods in Senegal (Tschakert, 2007), drought in the Sahel (Sissoko *et al.*, 2011) and Northwest China (Li *et al.*, 2013), and cyclone-related saltwater intrusion in coastal Bangladesh (Rabbani *et al.*, 2013). However, within rural areas, it is unclear whether poor people are more exposed than non-poor people. For instance, areas of higher forest cover loss might have lower poverty rates due to the income-generation opportunities associated with agricultural expansion or forest products (Chomitz *et al.*, 2007; Laurance *et al.*, 2014).

In urban areas, the differences in exposure between poor and urban households could be more pronounced. Land scarcity is more pressing in urban areas, such that poor people (especially migrants) tend to locate in cheaper parts of the city and end up in slums (Fay, 2005). Often, these slum areas are characterized by higher environmental risks which are reflected in the price of land (Fay, 2005): for instance, Lall and Deichmann (2012) observe that the parts of Bogota which experience the highest earthquake risk are also the cheapest, and are where most of the poor locate. Accordingly, Winsemius *et al.* (2015) find a positive association between flood risk and poverty within urban areas, but do not find the same association at the national level, suggesting land prices to play a key role in determining exposure to environmental risks in cities.

More generally, differences across poverty levels in rural-urban settings may reflect the differing role of natural resources: whether they are primarily an input to production or to environmental quality (Panayotou, 2016). For instance, forests may be used as a production input in rural areas so that they become increasingly degraded with higher wealth levels. In urban areas they may be seen as an environmental quality amenity and hence become more protected with higher wealth levels. While these differing roles of natural resources, such as forests, can help explain findings in previous studies, such a framework cannot be used for all the environmental risks which we explore in this paper.

In this context, it is of interest to understand whether poor people live in riskier places in rural and urban areas alike. Hence our third research question (RQ3) focuses on the difference in the relationship between environmental risks and poverty within rural and urban areas: Is the correlation between environmental risks (R) and poverty (P) positive (or negative for consumption levels) in rural as well as urban areas?

$$\text{corr}\,(R_{\text{Rural}}, P_{\text{Rural}}) > 0 \text{ and corr}\,(R_{\text{Urban}}, P_{\text{Urban}}) > 0 \tag{3}$$

2.3 Different causes

So far, we have discussed whether there is a positive relationship between environmental risks and poverty, but not the reasons behind this relationship. There can be multiple, interlinked channels that determine this relationship.

First, poor people and fragile areas could have shared vulnerabilities (Barrett *et al.*, 2011). For example, adverse hydroclimatic conditions could increase flood and drought hazards as well as ecosystem fragility, while also making livelihood activities, such as agriculture, more difficult, thereby resulting in lower incomes and consumption. For instance, dry climate zones in sub-Saharan Africa are vulnerable to precipitation deficits due to poor soils with low moisture storage capacity and host rural people who remain poor as they are reliant on low-return and high-risk agricultural activities (Zimmerman and Carter, 2003; Barrios *et al.*, 2010).

Second, poverty and environmental risks can be determined by common factors, such as institutional and market failures (Duraiappah, 1998; Barbier, 2010; Barrett *et al.*, 2011). For example, where property rights for land are missing, it is more likely that environmental resources, such as timber and fish, are overexploited (Baggio and Papyrakis, 2010). At the same time, powerful actors can oust poor people without land title from land, leaving them without their main asset for wealth accumulation (Grainger and Costello, 2014). These institutional failures can also be related to market failures, where environmental services, such as water and soil regulation, are not factored into market prices. While this lack of a price signal can lead to an underprovision of these services and hence higher risks, poor people managing ecosystems sustainably are not paid for this service provision.

Third, poverty could increase environmental risks (Duraiappah, 1998; Barbier, 2010; Barrett *et al.*, 2011). Many poor people – especially those in rural areas – depend on ecosystems for their livelihoods. For example, a systematic analysis of a 28-country data set shows that in (sub-) tropical smallholder systems, the poorest households derive more than half of their income from ecosystems and that this share is higher than for the wealthiest households (Angelsen *et al.*, 2014; Noack *et al.*, 2015). These incomes often play a role in consumption smoothing between seasons or as a coping mechanism when other incomes fail (Locatelli *et al.*, 2012). Although environmental extraction may not be a primary coping strategy (Wunder *et al.*, 2014), ecosystem-based incomes are a substitute for other incomes and can stabilize total incomes when weather anomalies hit (Noack *et al.*, 2015). In addition, where poor people lack other opportunities, they may disproportionally resort to overexploiting natural resources (e.g., timber, fish or grassland) for short-term survival – a strategy that can cause poverty traps (Barbier, 2010; Barrett *et al.*, 2011).

Fourth, environmental risks could increase poverty (Duraiappah, 1998; Barbier, 2010; Barrett *et al.*, 2011). Where people depend on ecosystems as a safety net or for their base income, any environmental risks that undermine these functions will reduce their incomes and consumption. In (sub-)tropical smallholder systems, an additional 13 per cent of households would be in poverty without ecosystem-based incomes (Noack *et al.*, 2015). Moreover, the occurrence of natural disasters can have a direct impact on welfare, pushing people back into poverty or making it harder for poor people to escape poverty: for instance, in Bolivia, poverty rates increased by 12 per cent in Trinidad city after the 2006 floods (Perez-De-Rada and Paz, 2008; Hallegatte *et al.*, 2017). Households that lack ex-post coping mechanisms often seek to mitigate risks ex-ante, for example through income diversification, thereby lowering average consumption and income (Bandyopadhyay and Skoufias, 2015). The extent to which the exposure to risks, without

the materialization of an immediate direct impact on consumption and incomes, such as forest or land degradation, can affect poverty has been less explored, and links are difficult to disentangle due to feedback loops and synergistic effects (Gerber *et al.*, 2014). Where the exposure to such risks has a negative effect on consumption and incomes, it is important to not only focus on risk response, but to derive strategies for risk reduction.

Hence it is important to understand whether risk exposure increases poverty or reduces consumption and income growth. While the other channels of the environment-poverty nexus are not less important, our fourth research question (RQ4) focuses on this channel[3]: do environmental risks (R) increase poverty (P) (or reduce consumption)?

$$P = f(R) \text{ or } R \rightarrow P \tag{4}$$

3. Data

This study combines socioeconomic data from the Living Standard Measurement Surveys (VHLSS) in 2010, 2012, and 2014 measuring household-level consumption, and recent geo-spatial data measuring environmental risks at high resolution. These two data types are merged at the district and commune levels.

3.1 Socioeconomic data

The VHLSS 2010, 2012, and 2014 are nationally and regionally representative and contain detailed information on individuals, households and communes.[4] In total 9,400 households nationwide are included in each round. A particularity of the VHLSS data is that half of these households were interviewed in two or three of these survey years. These households form a short-term 'Panel' dataset to explain consumption changes over time. Other households were only observed in one of the three years. Using these cross-section data, treating all observations as independent observations provides a 'Pooled' dataset to explain consumption differences between households. In rural areas, 6,600–6,750 households from about 2,200 communes in each year are included ('Pooled' cross section). Of these, 1,400 are observed in all three rounds, 1,600 are observed in 2010 and 2012, and 1,400 are observed in 2012 and 2014 ('Panel' dataset). In urban areas, the dataset covers 2,650–2,780 households in each year from 900 communes ('Pooled'). Of these, 500 are in all three rounds, 575 in 2010 and 2012, and 640 in 2012 and 2014 ('Panel').

The VHLSS data provide detailed information to estimate consumption values based on expenditure data. Section 4 uses district-level poverty maps. The ratio and number of people below the national poverty line[5] in each district is estimated using the consumption values from the VHLSS 2010 combined with the 15 per cent sample of the 2009 Population and Housing Census as calculated by Lanjouw *et al.* (2013). Sections 5 and 6 use consumption values from the VHLSS 2014 and section 7 adds the data from the 2010 and 2012 surveys. All consumption values are calculated in line with the methodology for determining the national poverty line.[6]

---

[3]We also lack data to investigate the other three channels.

[4]These surveys are conducted by the General Statistics Office (GSO) with technical support from the World Bank in Vietnam.

[5]The national poverty line as calculated by GSO and the World Bank is used.

[6]All consumption values are expressed in 2011 purchasing power parity (PPP) values using data on the Consumer Price Index from the World Development Indicators.

This data from Lanjouw *et al.* (2013) is used to examine RQ1. Through our own calculations, we use the 2014 VHLSS to examine RQ2 and RQ3, while we use all three rounds (2010, 2012, and 2014) to examine RQ4.

The household and commune surveys in the VHLSS 2010, 2012, and 2014 also include a wide array of data on socioeconomic conditions. Data at the individual level include demographics, education, employment, health and migration. At the household level, data comprise information on durables, assets, production, income and participation in government programs. The commune surveys collect information about the commune characteristics including access to land, infrastructure and services. Based on these data, a number of socioeconomic controls are constructed for the analyses based on household and commune surveys (the summary statistics can be found in the online appendix, table A.1).

3.2 Environmental risk data

Based on geo-spatial datasets, variables are constructed to measure environmental risk at district and commune levels representing eight environmental risks. These variables are based on historical risk profiles measuring the area's exposure to fragile and severe conditions and not the actual environmental conditions at the time of the VHLSS surveys. The following variables are calculated to measure the area-weighted average of each environmental risk at the district and commune level (the summary statistics can be found in table A.1)[7]:

(1) **Air pollution** is measured by the area-weighted mean of concentration (measured as micrograms per cubic meter) of particulate matter with a diameter of 2.5 micrometers or less (PM2.5) taking the 10 year-average value for 2000–2010. The data is based on satellite imagery using the total column aerosol optical depth from the Moderate Resolution Imaging Spectroradiometer (MODIS) and Multiangle Imaging Spectroradiometer satellite instruments, which is combined with chemical transport model simulations, and ground measurements from 79 countries to produce a global spatial dataset with 0.1×0.1 resolution (Brauer *et al.*, 2015). PM2.5 includes dust, dirt, soot, smoke and liquid droplets, which can lodge deeply into the lungs due to their small size. PM2.5 air pollution has been identified as a leading risk factor in diseases globally (Forouzanfar *et al.*, 2015) as well as in Vietnam (Luong *et al.*, 2017).

(2) **Tree cover loss** is calculated as the share of the area under tree cover in 2000 that suffered from a tree cover loss between 2000 and 2010. Tree cover is defined as canopy closure for all vegetation taller than 5 m in height and is calculated from imagery from the Landsat 4, 5, 7, and 8 satellite data used to produce a global forest cover change map (Hansen *et al.*, 2013). Tree cover loss can be associated with a habitat disturbance and ecosystem service disruptions, which can make human landscapes more fragile to other impacts (Sodhi *et al.*, 2010). It can also undermine the livelihoods of poor people highly dependent on forest timber and other resources (Angelsen *et al.*, 2014).

(3) **Land degradation** is measured by the share of land area that experienced a significant biomass decline. This loss is calculated based on the inter-annual

---

[7]For the weather and temperature variability, due to the coarse resolution of the data, the value of the centroid of the commune is taken to represent these risks (rather than the area-weighted average).

mean trend of Normalized Difference Vegetation Index based on data from the Advanced Very High Resolution Radiometer (AVHRR) of the National Oceanic and Atmospheric Administration (NOAA) satellite between 1982 and 2006, which is corrected for climate effects to only measure human-induced degradation (Vu *et al.*, 2014b). Soil ferti lity, agricultural productivity and ultimately food security of smallholder farmers can be largely compromised on degraded lands (Von Braun *et al.*, 2013).

(4) **Slope** is measured by the area-weighted average of slope categories. This variable is calculated based on data from the Harmonized World Soil Database version 1.2 with eight slope classes: 1 for least steep (elevation of 0–0.5 per cent) and 8 for most steep slope (elevation greater than 45 per cent).[8] Steep slopes are much more prone to surface water runoff and soil erosion – particularly in areas affected by heavy rainfalls and tree cover loss (Sidle *et al.*, 2006; Vezina *et al.*, 2006). At the same time, tropical cyclones can cause fatal landslides, which already result in significant loss of life in mountainous areas of South and East Asia (Petley, 2010; 2012).

(5) **Rainfall variability** is defined as the 1981–2010 standard deviation of monthly rainfall levels measured in millimeters (mm). The variable is constructed from the global CRU TS3.21 dataset from the University of East Anglia, containing a long-term time series of monthly rainfall levels at 0.5×0.5 grid resolution, which was produced using statistical interpolation based on data from 4,000 weather stations (Harris *et al.*, 2014). Higher historic rainfall variability indicates higher inter-annual and intra-annual variation of precipitation and a higher incidence of extremely wet and dry conditions. In Vietnam, excessive rainfall can have negative income effects for poor households, while wealthier households are more negatively affected by the lack of rainfall (Narloch, 2016).

(6) **Temperature variability** is measured by the standard deviation of mean annual temperatures across the time period 1981–2010 in degrees Celsius (C). The underlying data also comes from the global CRU TS3.21 dataset including a long-term time series of monthly mean temperature values at 0.5×0.5 grid resolution. Temperature variability indicates varying temperature conditions between seasons and years and a higher incidence of heat waves and cold spells. In Vietnam, hot conditions generally have an income-reducing effect for rural households (Narloch, 2016).

(7) **Flood hazards** are represented by the share of area at risk of a flood event (inundation depth >0) with a 25-year return period under historical conditions.[9] The measures are based on the inundation depth, estimated by state-of-the art flood models at a grid cell level of 3 arc-seconds combining coastal surge hazard layers, along with pluvial and fluvial layers (Bangalore *et al.*, 2016). In Vietnam, flood events have been shown to significantly reduce welfare and increase poverty (Thomas *et al.*, 2010; Bui *et al.*, 2014; Arouri *et al.*, 2015).

(8) **Drought hazards** are measured by the area-weighted intensity of drought conditions. This intensity is a measure of hydrological droughts and is expressed by the number of months of long-term mean discharge which would be needed to

---

[8]See http://www.fao.org/soils-portal/soil-survey/soil-maps-and-databases/harmonized-world-soil-database-v12/en/ for more details.

[9]A 25-year return period corresponds to 0.04 annual probability of occurrence.

overcome the maximum accumulated deficit volume during dry months (Winsemius *et al.*, 2015). Drought events in Vietnam are associated with agricultural production losses, negative welfare impacts and poverty (Thomas *et al.*, 2010; Bui *et al.*, 2014; Arouri *et al.*, 2015).

3.3 *Data limitations*

There are several limitations in using these datasets for the purpose of this study. Nevertheless, these data allow us to provide some interesting insights into our research questions.

First, while the data is representative of socio-economic conditions of the entire country, its eight regions and rural and urban areas, it is not representative of the different environmental risk profiles across communes. Building the living standard measurement survey (LSMS) methodology, the sampling strategy follows a three-stage stratified cluster design, whereby about one-third of all communes are selected and divided into three areas from which one area is chosen and three households are interviewed from these areas (ISM and SINFONICA, 2015). Due to this strategy, the entire variety of communes is not represented and communes in very remote areas and with extreme risk profiles – for example, those in remote mountainous areas, natural forests or islands – may not be captured at all or may be underrepresented. This sampling bias could lead to an underrepresentation of very high risks areas.

Second, all the environmental risks variables on hand are time-invariant (i.e., they have the same value for all the years with household survey data) as they are based on historic risk profiles. On the one hand, it would be preferable to measure actual conditions during the survey years to control for any changes between the years, which is not possible as such data was not available when this study was prepared. On the other hand, measuring environmental risks based on past conditions minimizes causality problems, whereby consumption and income can determine current environmental conditions. However, the data cannot address any omitted variables bias, which leads to some endogeneity concerns (as will be discussed in section 5).

Third, most of the environmental risks variables are based on global datasets using global models or data, which are not necessarily representative of the specific conditions within the districts and communes in Vietnam. Optimally such variables would be measured based on ground station data, which however is not readily available. Although these are important limitations that require further work, the available data can provide some first insights into the relationships between environmental risks and poverty.

4. Incidence of poverty in low- and high-risk districts

The following spatial analysis addresses the first research question (RQ1) which explores whether the incidence of poverty is higher in high risk districts than in low risk districts. Although the exposure of poor people to environmental conditions depends on their exact location in the district, such a district-level analysis helps to identify spatial hotspots where poverty coincides with high environmental risk levels.

4.1 *Methods*

National maps are produced that show the extent of environmental risks and poverty at the district level. Based on the 2010 poverty rate maps from Lanjouw *et al.* (2013), all

districts are classified into high, medium, or low poverty categories with an equal number of districts in each group, using the poverty rate (i.e., relative poverty) and number of poor people (i.e., absolute poverty) in each district. Similarly, all environmental risk variables are separately calculated at the district level to categorize districts into high, medium and low risk districts.[10]

We chose this relative categorization (three terciles for each environmental risk, with equal number of districts in each category), since guidance in creating risk-specific categories was largely unavailable. While thresholds exist for air pollution, based on guidance from the WHO which allows categorization into low, medium, and high (Brauer *et al.*, 2015), the other seven environmental risks do not have clear guidelines on threshold values. Rather than create our own threshold values, we decided on a relative approach to split the districts evenly into three terciles for each risk, consistent with the poverty categorization. We are unaware of published studies creating similar 'bivariate choropleth' maps in this field, although a recent paper on poverty and access to healthcare follows the same categorization rule that we choose (Tansley *et al.*, 2017). Given that our RQ1 aims to examine the confluence of poverty and risk (e.g., high poverty and high risk districts), we argue that this categorization is suitable. The environmental risk maps are then overlaid with the relative (figure 1, panel a) and absolute poverty maps (figure 1, panel b). In addition, the poverty rate and number of poor people in each risk category is calculated (table 1 and online appendix, table A.2).

4.2 Results

Across Vietnam there is considerable spatial variation in poverty and environmental risks and there are some large hotspots of high environmental risks and poverty. As indicated by the dark districts in the maps (figure 1, panel a), northern districts face a combination of high poverty and high air pollution, tree cover loss, steep slopes, temperature variability and drought hazards. In the Central Highlands, tree cover loss, steep slopes and rainfall variability are higher in poorer districts. And in the Mekong River Delta, there are a few poorer districts that face high land degradation, flood and drought hazards. When looking at absolute poverty numbers, a few shifts in these patterns emerge from sparsely populated districts, as for example, in the Central Highlands, to districts with larger concentrations of poor people (figure 1, panel b).

Generally, in high risk districts the poverty rate is higher than in low risk districts. The difference is most pronounced for tree cover loss and slope, but also significant for all the other environmental risks (table 1). Only for flood hazards, is poverty significantly higher in low risk districts than in high risk districts. This observation can be explained by the higher incidence of flood hazards in prosperous coastal regions and river deltas (figure 1, also see Bangalore *et al.*, 2016).

Similarly, a large number of people below the poverty line are concentrated in high risk areas. Also the number of poor people is significantly higher in high risk than in low risk areas, with an average of about 30,000 people living in districts with high tree cover loss and land degradation, steep slopes and high drought hazards (compared to

---

[10]For land degradation, due to the large number of districts experiencing no loss (0), the low risk category includes all districts with 0 loss (243 districts), and the rest of the districts are split into the medium and high categories.
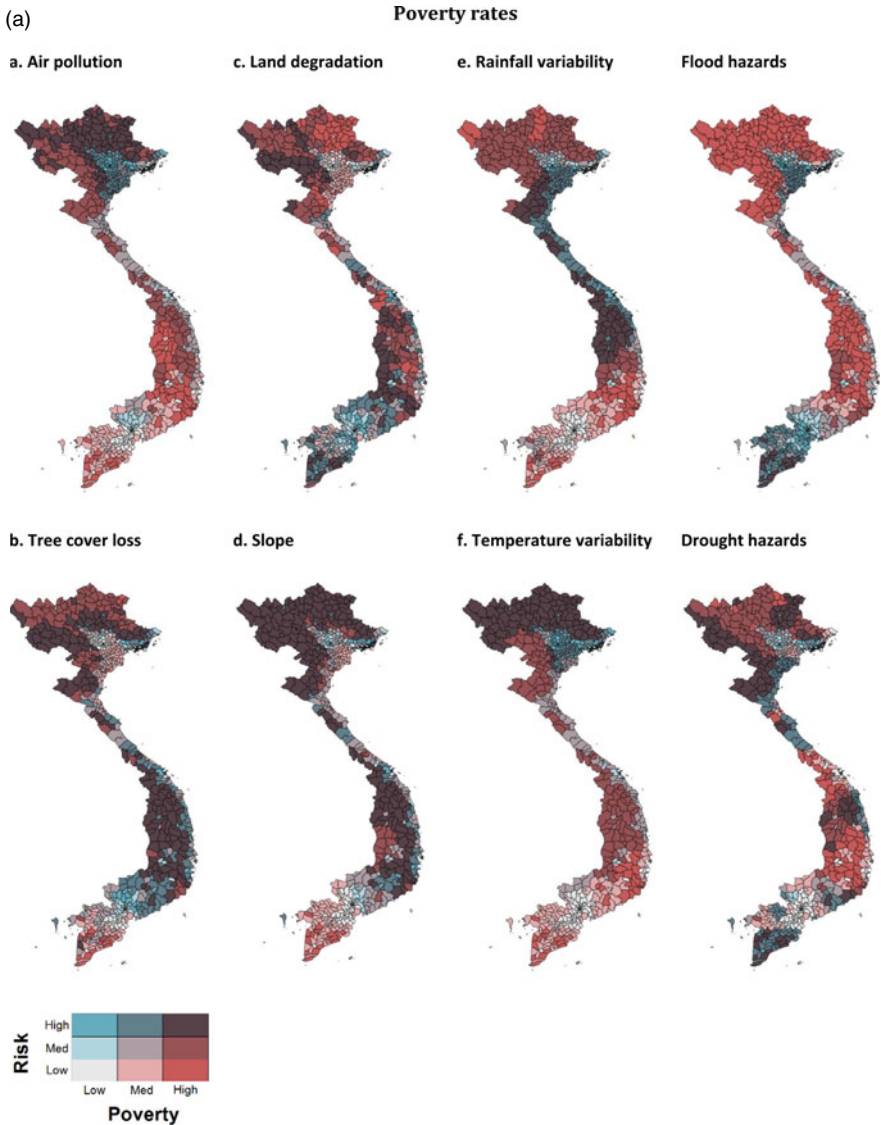
(a)   **Poverty rates**

Figure 1. Overlay of poverty in 2010 and environmental risk categories at the district level. (a) *Poverty rates*, (b) Number of poor people.

Notes: The figures show the district-level overlay of poverty and environmental risks maps. Panel a shows the rate of people in each district below the national poverty line with Poverty- Low = <14%, Medium = 14–28%, High = >28%. Panel b shows the number of people in each district below the national poverty line with Poverty – Low = <15,000, Medium = 15,000–29,000, High = >29,000. Districts are classified based on the following categories for environmental risks (calculated as three terciles, with equal number of districts in each category): Air pollution – Low = <9.11, Medium = 9.11–23.75 High = >23.75 based on area-weighted PM2.5 pollution levels (micrograms per cubic meter); Tree cover loss – <0.21, Medium = 0.21–2.28 High = >2.28 based on share of forest area affected by tree cover loss; Land degradation – Low = 0, Medium = 0.01–20.14 High = >20.14 based on area share affected by biomass loss; Slope – Low = <2.7, Medium = 2.7–5.3 High = >5.3 based on area-weighted average of slope category; Rainfall variability – <45.50, Medium = 45.50–61.44 High = >61.44 based on the long-term standard deviation of monthly rainfall; Temperature variability – <0.61, Medium = 0.61–0.85
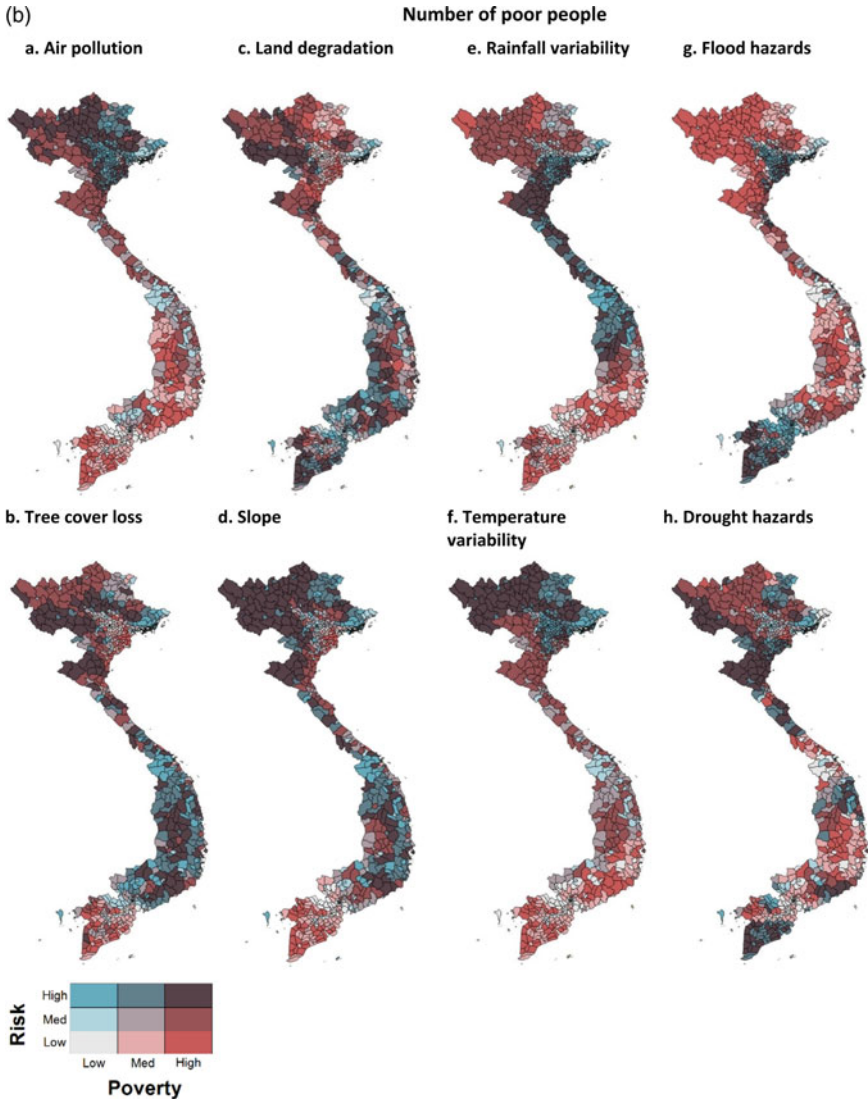
(b)
Number of poor people

a. Air pollution   c. Land degradation   e. Rainfall variability   g. Flood hazards

b. Tree cover loss   d. Slope   f. Temperature variability   h. Drought hazards

Figure 1. (*Continued.*)
High = >0.85 based on based on the long-term standard deviation of monthly mean temperature; Flood hazards: Low = <10%, Medium = 10–30%, High = 30% > based on the area shared at risk of a 25-year return period flood; Drought hazards: – <0.87, Medium = 0.87–1.04 High = >1.04 based on number of months to overcome water deficit during dry months.
Source: Authors' calculation based on poverty data from VHLSS 2010 based on Lanjouw *et al.*, 2013, and environmental data from Hansen *et al.*, 2013; Vu *et al.*, 2014a, b; Brauer *et al.*, 2015, Harmonized World Soil Database, Climate Research Unit, Winsemius *et al.*, 2015; Bangalore *et al.*, 2016, and Geographic Information Science and Technology, 2015.

20,000 people in low risk districts) (table A.2). And an average of 20,000 people live in districts with high flood hazards, implying that floods can still affect a large number of poor people, even though they affect relatively wealthier districts.

Table 1. Poverty rates in 2010 across environmental risk categories at district level

Risk category	Air pollution	Tree cover loss	Land degradation	Slope	Rainfall Variability	Temperature Variability	Flood hazards	Drought hazards
Low	21.3%	13.5%	19.5%	14.6%	20.6%	18.0%	49.1%	21.4%
Medium	33.2%	29.1%	32.6%	16.8%	35.6%	32.2%	16.7%	28.3%
High	26.9%	38.6%	30.0%	49.7%	25.5%	31.5%	15.4%	31.6%
ANOVA F	16.83	92.14	24.11	361.41	28.49	31.56	322.54	12.71
Prob>F	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Notes: This table shows the poverty headcount rate across the three environmental risks categories as calculated for figure 1 and statistics from a one-way analysis-of-variance (ANOVA), which assess whether the difference in poverty rates across risk categories is statistically significant.
Source: Authors' calculation based on poverty data from the VHLSS 2010 based on Lanjouw *et al.*, 2013, and environmental data from Hansen *et al.*, 2013; Vu *et al.*, 2014b; Brauer *et al.*, 2015, Harmonized World Soil Database, Climate Research Unit, Bangalore *et al.*, 2016, and Winsemius *et al.*, 2015.

5. Risks among different household groups

This section addresses the second research question (RQ2) which explores whether environmental risks at the commune level are significantly different between household groups. Although there can be considerable variation in environmental conditions within communes, environmental risks measured at the commune level can measure the wider environmental risk households are exposed to.[11]

5.1 Methods

To compare environmental risks across households, the level of environmental risks is calculated for each commune. Whereas the geographical location of communes is known, the household data from the VHLSS is not geo-coded so it is not possible to track the exact location of households within communes. In addition to the commune-level absolute risk value, the standardized value of each environmental risk is calculated.[12] Such normalization produces a scaled version of the original value which allows comparison between the different risk variables. The absolute values (table A.3) and standardized values (figure 2) are then compared across household groups in 2014, distinguishing between (i) households from ethnic minorities versus non-minorities, (ii) households below ('poor') and above the poverty line ('non-poor'), (iii) households in the bottom two consumption quintiles ('b40') and the top three consumption quintiles ('t60'), and (iv) households in rural ('rural') and urban ('urban') areas.

5.2 Results

There are considerable differences in risk profiles between different groups. Households from ethnic minorities, those below the poverty line and those in the lowest two consumption quintiles live in much riskier communes (figure 2). It can be seen that

---

[11]Furthermore, as communes are about one-fifth of the size of districts, there is likely to be considerably less variation in environmental risk within communes than within districts.

[12]From each commune value the mean is subtracted and divided by the standard deviation, producing a value distribution with a mean of 0 and a standard deviation of 1.
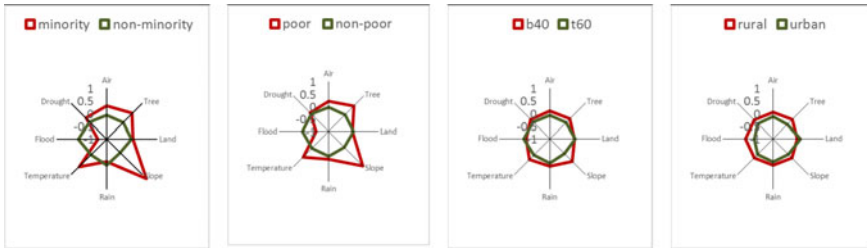
Figure 2. Environmental risk profiles across socio-economic groups in 2014.

Notes: Spider diagrams show the mean risk values of households in each socio-economic group: households that belong to ethnic minorities (Minority), households below the national poverty line (Poor), the households in the lower two consumption quintiles (Bottom40), and households in the upper three consumption quintiles (Top60). Environmental risk values are standardized by subtracting their mean and dividing by the standard deviation. Descriptive statistics of all environmental risks variables with original units are shown in table A.1.

Sources: Authors' calculation based on socio-economic data from VHLSS 2014 and environmental data from Hansen *et al.*, 2013; Vu *et al.*, 2014b; Brauer *et al.*, 2015, Harmonized World Soil Database, Climate Research Unit, Bangalore *et al.*, 2016, and Winsemius *et al.*, 2015.

the differences are most pronounced for the minority versus non-minority households. Poor households have a similar risk profile also because more than 50 per cent of poor households belong to ethnic minorities. Accordingly, households that face marginalization due to poverty or ethnicity are also disproportionally exposed to multiple, possibly interlinked, environmental risks.

For most environmental risks the differences between groups are significant. Ethnic minorities, poor households and those in the lowest two consumption quintiles face much higher air pollution, tree cover loss, steeper slopes, rainfall and temperature variability and drought hazards compared to their wealthier counterparts (table A.3). They are, however, exposed to lower flood hazards, confirming results from section 3 that flood risks are higher in more prosperous districts. These risk levels are very similar among groups in 2010, 2012 and 2014, suggesting that movement out of high risk zones has remained very limited over time (Narloch and Bangalore, 2016).

Looking at differences between rural and urban households, aside from land degradation, all other risk levels are much higher (table A.3) in rural households. Accordingly, the general risk profile is also more extreme for rural than urban households (figure 2). This finding is expected, as most of the ethnic minorities, poor households and those in the lowest consumption quintiles are rural households. Yet this finding does not imply that within rural or urban areas, poorer households are also more exposed than their wealthier counterparts, which will be further analyzed in the next section.

6. Risks and poverty within rural and urban areas

This section addresses the third research question (RQ3) which touches upon the last section to show whether the relationship between environmental risks at the commune level and household-level consumption levels is different between rural and urban areas.

6.1 Methods

The data is split into a rural and urban subsample to calculate correlation coefficients and run nonparametric analyses. For both sub-samples, the correlation coefficient between

household-level consumption based on the expenditure data from the VHLSS 2014 and commune-level risks variables is calculated (table A.4). Households are further divided into consumption percentiles (100 groups) to show the mean level of consumption (*x*-axis) and of environmental risks (*y*-axis) for each percentile for the rural and urban sub-sample (figure 3).

6.2 Results

In both rural and urban areas, poorer households tend to live in communes with higher environmental risks. While for most environmental risks the correlation with per capita consumption is negative within rural as well as urban areas, the degree of correlation varies between rural and urban areas (table A.4). In rural areas, households in the lower percentiles are more exposed to air pollution, tree cover loss, steep slopes, rainfall and temperature variability, but less exposed to flood hazards (figure 3). In urban areas, poorer households are more concentrated in areas with high tree cover loss, slope, flood and drought hazards, while living in places with lower air pollution and temperature variability (figure 3).

Some remarkable differences emerge between rural and urban areas (figure 3 and table A.4). Poorer households seem to be less exposed to flood hazards in rural areas, but more so in urban areas. This finding could reflect the fact that many of the rural poor live in the mountainous areas where flood hazards are generally lower than in low-lying but wealthier river deltas and coastal zones, while many of the urban poor are pushed into high risk areas due to land constraints in the cities. This finding is consistent with a recent global analysis of flood exposure and poverty in 52 countries, which reports ambivalent results for flood exposure at the country level, but shows a strong signal of over-exposure of the poor when only focusing on urban areas (Winsemius *et al.*, 2015). Also poorer households are more exposed to air pollution and temperature variability in rural areas, but less in urban areas. Possibly, wealthier households live in rapidly developing urban areas with heavy traffic and industrial congestion, thereby being more exposed to air pollution.

7. Environmental risks and consumption differences and changes

To address the fourth research question (RQ4), this section investigates how environmental risks relate to consumption differences between households and consumption changes over time, applying a set of regression models. Notwithstanding several limitations, these analyses help provide first insights into the causal relationship between environmental risks and poverty.

7.1 Methods

Two sets of regression models are fitted to estimate the effect of environmental risks on consumption differences between households in the 'Pooled' cross-section and on consumption changes over time for the 'Panel' dataset. Using Ordinary Least Squares (OLS) estimators the following equation is fitted in the *Pooled* and *Panel* models:

$$Y_{i_{j_t}} = \alpha + \beta R_j + \delta Z_j + \omega W_{j_t} + \gamma X_{i_{j_t}} + \lambda T_t + u_{i_{j_t}},$$

where *Y* denotes per capita consumption observed for household *i* in commune *j* in year *t* (i.e., 2010, 2012, 2014) in the *Pooled* model and the change in per capita consumption
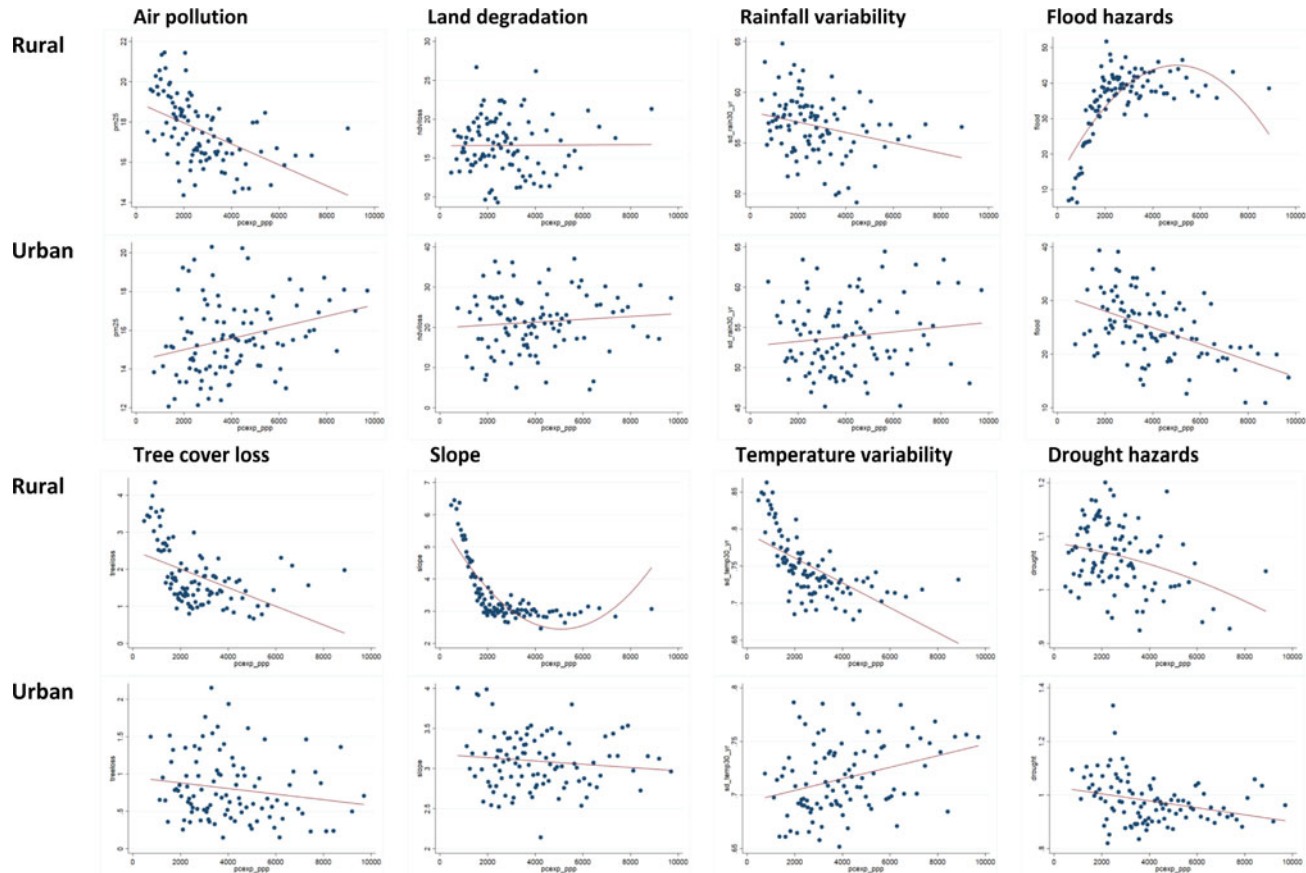
Figure 3. Environmental risks across consumption percentiles within rural and urban zones in 2014.
Notes: Binned scatterplots show the non-parametric relationship between consumption and environmental risks with each data point representing a consumption percentile. *X*-axis shows the mean level of per-capita expenditure in 2014 (e.g. measure of poverty) for each percentile. *Y*-axis indicates the mean level of environmental risks for each percentile.
Sources: Authors' calculation based on socio-economic data from VHLSS 2014 and environmental data from Hansen *et al.*, 2013; Vu *et al.*, 2014b; Brauer *et al.*, 2015, Harmonized World Soil Database, Climate Research Unit, Bangalore *et al.*, 2016, and Winsemius *et al.*, 2015.

for household *i* between years *t* (i.e., 2010–2012 and 2012–2014) in the *Panel* model. *R* measures the environmental risk profile in commune *j*, which is time-invariant, as described in section 2.2. β is the parameter of interest that indicates the consumption effect of environmental risks. *Z* includes commune-specific geo-spatial controls that do not change over time, such as proximity to cities and roads and the long-term average of rainfall and temperature. *W* includes a set of time-variant commune variables measured by rainfall and temperature levels in the survey years 2010, 2012 and 2014 for the *Pooled* model and by the change for 2010–12 and 2012–14 for the *Panel* model. *X* is a set of household-specific controls that vary over time, such as the levels of education, labor and land endowments in survey years for the *Pooled* model and the difference between years for the *Panel* model. *X* also includes time-invariant demographic characteristics, such ethnicity and gender.[13] *T* measures time-fixed effects to neutralize common trends over time. *U* is a random, idiosyncratic error term. The descriptive statistics of these variables are provided in table A.1.

A main concern when fitting models to estimate weather impacts on economic outcomes is endogeneity bias. Problems of reverse causation (e.g., high consumption growth in one place leading to environmental depletion) are minimized by taking the historic risk profile and not measuring actual environmental conditions in the survey years. Yet the model is likely to suffer from omitted variable bias caused by the potential correlation of risk variables with other commune characteristics that determine living standards.[14] To minimize omitted variable bias in this study, a set of observable commune characteristics is included that are likely to influence risk profiles and living standards, such as average rainfall and temperature conditions and distance from cities and roads. Nonetheless, to the extent that other, non-observable commune characteristics also determine risks and consumption, the estimates of β are biased. For instance, some communes may differ on the level of trust, which is likely to be associated with higher living standards and better environmental outcomes. In this case, our estimates would be biased upwards.

These regression models are estimated for various sub-samples to disentangle varying effects between groups, zones and years. For both the *Pooled* and *Panel* models, we first estimate the consumption effect one-by-one and then include all risk variables altogether. While only the results of the latter are presented, most of the results hold in the models with only one risk variable. Robust standard errors are estimated by clustering at the commune level in order to account for spatial correlation. For the *Pooled* model, the natural logarithm of per capita consumption is used in the regression to normalize the skewed distribution of consumption (i.e., many observations of low consumption levels and a few observations of very high consumption levels).[15]

---

[13]The datasets allow us to control for land and labor inputs of some activities. These are, however, not included in the regression analyses due to potential endogeneity biases, as higher risks also determines land and labor inputs.

[14]This omitted variable bias could be minimized by fitting a fixed-effects linear model using a within-regression estimator based on the Panel dataset as in Narloch (2016). Yet such a model does not allow us to disentangle the impact of time-invariant risk factors, such as the environmental risk variables, so it cannot be applied for the purpose of this study.

[15]Taking the natural logarithm also improves the explanatory power of the various models and brings ease in interpreting the coefficients as a percentage change of the outcome variable.

Table 2. The effect of environmental risks on consumption differences between 'Pooled' households in 2010, 2012 and 2014

	Dependent variable: Ln of per-capita expenditure						
	All	Poor	B40	Rural	Rural 2014	Urban	Urban 2014
Air pollution	0.000511	0.00176	**0.00255****	**0.00425*****	0.00220	−0.00178	−0.00315
	(0.32)	(1.01)	(2.18)	(2.60)	(1.14)	(−0.55)	(−0.81)
Tree cover loss	−0.00179	0.00229	−0.00125	0.00132	−0.00248	−0.00705	−0.00500
	(−1.18)	(1.60)	(−1.10)	(0.88)	(−1.37)	(−1.35)	(−0.74)
Land degradation	**0.000300***	−0.000256	0.000171	0.000108	0.000197	−0.0000844	−0.00000728
	(1.87)	(−1.27)	(1.26)	(0.55)	(0.81)	(−0.33)	(−0.02)
Slope	**−0.0213*****	**−0.0148****	**−0.0102****	**−0.0101***	−0.00389	−0.0164	−0.0117
	(−3.98)	(−2.32)	(−2.43)	(−1.71)	(−0.55)	(−1.58)	(−0.88)
Rainfall variability	**−0.00276*****	−0.00120	−0.000420	**−0.00281*****	**−0.00499*****	−0.000672	−0.000577
	(−4.48)	(−1.46)	(−0.75)	(−4.21)	(−4.73)	(−0.58)	(−0.33)
Temperature variability	**−0.265***	0.0382	**−0.212***	**−0.454*****	−0.0311	0.113	0.318
	(−1.88)	(0.22)	(−1.68)	(−2.98)	(−0.17)	(0.42)	(0.95)
Flood hazard	**−0.00144*****	−0.000202	0.00000600	0.000183	0.000441	**−0.00184*****	**−0.00201*****
	(−5.97)	(−0.74)	(0.04)	(0.67)	(1.43)	(−4.05)	(−3.96)
Drought hazard	**−0.0335*****	0.00353	**−0.0199****	**−0.0428*****	**−0.0379****	−0.0380	−0.0477
	(−2.67)	(0.26)	(−2.01)	(−3.17)	(−2.29)	(−1.59)	(−1.56)

(continued)

Table 2. Continued

	All	Poor	B40	Rural	Rural 2014	Urban	Urban 2014
	Dependent variable: Ln of per-capita expenditure						
Control variables (results In table A.5)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
_cons	8.024***	6.487***	6.849***	7.513***	6.677***	7.580***	7.225***
	(35.15)	(25.99)	(32.66)	(30.26)	(20.11)	(18.23)	(13.23)
N	27698	3811	11025	19748	6492	7950	2715
R²	0.432	0.204	0.365	0.399	0.409	0.316	0.305

Notes: This table indicates coefficients estimated from 'Pooled' Cross-section model using Ordinary Least Squares. *0.10, **0.05, ***0.01 significance level. Values in parentheses indicate standard errors corrected for cluster correlation at the commune level. B40 denotes households in the bottom two consumption quintiles. Controls include current rainfall, current temperature, long-term rainfall, long-term temperature, distance city, distance road, area agriculture, area forest, area water surface, workforce, education, age head, female head, minority, year 2012, and year 2014. Full results (including for controls) presented in table A.5.

Source: Authors' calculation based on socio-economic data from VHLSS 2010, 2012 and 2014 and environmental data from Hansen *et al.*, 2013; Vu *et al.*, 2014b; Brauer *et al.*, 2015, Harmonized World Soil Database, Climate Research Unit, Bangalore *et al.*, 2016, and Winsemius *et al.*, 2015.

7.2 Results

Environmental risks are related to consumption differences between households. The results for environmental risks are presented in table 2, with the full results (including for all controls) shown in table A.5. Across all households from the Pooled cross-section, those households that live in communes with steeper slope, higher rainfall and temperature variability and flood and drought hazards have significantly lower consumption (table 2, column 'All'). Only for land degradation does there seem to be a positive relationship, which may indicate communes of intensive agricultural expansion and growth, which could be positively associated to wealth in the short term. This finding points to possible estimation biases from unobservable factors, which do not allow us to establish clear, causal relationships with these data.

Within the various groups, different risk factors matter for consumption levels. As differences in per capita expenditure between households below the poverty line are modest, it is not surprising that generally fewer variables are significant for the sub-sample of poor households and that the models have a much lower explanatory power (table 2, column 'Poor'). The role of environmental risks in explaining consumption differences for households in the lowest two consumption quintiles follow the overall pattern, but there is a significant positive relationship with air pollution (table 2, column 'B40'). The same finding emerges from the rural subsample (table 2, column 'Rural'). Possibly rural households in communes closer to urban centers are wealthier, while being more exposed to air pollution than their counterparts in remote rural areas. Whereas in rural areas slope, rainfall and temperature variability and droughts are negatively related to consumption, in urban areas floods have a significant negative effect (table 2, column 'Urban'), confirming the results in section 6. Very similar findings appear for the 2014 subsample, indicating that there are no considerable differences between the three survey years (table 2, columns 'Urban 2014' and 'Rural 2014').[16]

Changes in consumption over time are only related to a limited number of risk variables and some show unexpected signs. The results for environmental risks are presented in table 3, with the full results (including for all controls) found in table A.6. Temperature variability relates to significantly higher consumption growth, mainly driven by urban households between 2012 and 2014 (table 3, columns 'All' and 'Urban 2012–14'), while for households within the lowest two consumption quintiles, floods seem to have a positive effect on consumption growth (table 3, column 'B40'). These effects can capture favorable weather conditions between 2010 and 2014 in these risk prone areas. For example, as long as no flood or extreme heat occurs, people living in flood plains or hotter zones can benefit from more profitable activities, such as floating rice or coffee cultivation. Higher land degradation is positively related to consumption growth in the rural subsample (table 3, column 'Rural'). This effect may capture unobserved factors that facilitate higher consumption growth, such as non-farm income opportunities in more degraded areas.

Yet a number of risk variables are related to lower consumption growth between 2010 and 2014, indicating a negative effect. Households in communes with higher PM2.5 concentration levels have a significantly lower consumption growth (table 3, column 'All'). Lower consumption growth in 2012–14 is related to tree cover loss in rural zones and to rainfall variability in urban zones (table 3, columns 'Rural 2012–14' and 'Urban

---

[16]These results also hold when including the risk variables one-by-one and not the whole set.

Table 3. The effect of environmental risks on consumption changes over time of 'Panel' households in 2010–12 and 2012–14

	Dependent variable: Change in per-capita expenditure						
	All	Poor	B40	Rural	Rural 2012–14	Urban	Urban 2012–14
Air pollution	−**12.37***	6.040	−0.0273	−4.189	−3.224	−34.10	−41.43
	(−1.91)	(1.52)	(−0.01)	(−0.86)	(−0.42)	(−1.58)	(−1.61)
Tree cover loss	−4.166	−1.376	−5.865	−4.605	−13.16*	−0.818	−5.808
	(−0.73)	(−0.40)	(−1.63)	(−0.83)	(−1.92)	(−0.03)	(−0.11)
Land degradation	0.262	0.554	0.0442	**1.555****	0.542	−2.124	−2.237
	(0.33)	(0.96)	(0.09)	(2.13)	(0.47)	(−1.15)	(−0.72)
Slope	8.262	−17.99	4.052	−2.692	−1.030	38.90	67.10
	(0.43)	(−0.93)	(0.30)	(−0.16)	(−0.04)	(0.73)	(0.91)
Rainfall variability	−0.162	−**3.139***	0.445	−0.349	−0.132	−0.250	−**15.18***
	(−0.08)	(−1.71)	(0.32)	(−0.17)	(−0.04)	(−0.04)	(1.72)
Temperature variability	**974.5***	193.5	182.0	377.8	403.0	2582.1	**6247.0****
	(1.74)	(0.61)	(0.67)	(0.88)	(0.63)	(1.42)	(2.40)
Flood hazard	−0.390	0.110	**1.533****	−0.0430	−0.602	−4.244	−3.479
	(−0.38)	(0.10)	(2.33)	(−0.05)	(−0.45)	(−1.30)	(−0.99)
Drought hazard	−2.442	−**121.1****	−64.84	−35.65	53.63	137.7	58.11
	(−0.05)	(−2.06)	(−1.55)	(−0.72)	(0.67)	(0.89)	(0.23)

Table 3. Continued

	All	Poor	B40	Rural	Rural 2012–14	Urban	Urban 2012–14
	Dependent variable: Change in per-capita expenditure						
Control variables (results In table A.6)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
_cons	−1943.4**	188.1	−784.5*	−542.3	−1461.6	−5280.7**	−12451.3***
	(−2.25)	(0.39)	(−1.70)	(−0.73)	(−1.38)	(−2.17)	(−3.05)
N	7957	952	3250	5804	2792	2153	1109
R^2	0.017	0.171	0.076	0.020	0.035	0.029	0.050

Notes: This table indicates coefficients estimated from 'Panel' model using Ordinary Least Squares and differences over time for time-variant variables. *0.10, **0.05, ***0.01 significance level. Values in parentheses indicate standard errors corrected for cluster correlation at the commune level. B40 denotes households in the bottom two consumption quintiles. Controls include current rainfall, current temperature, long-term rainfall, long-term temperature, distance city, distance road, area agriculture, area forest, area water surface, workforce, education, age head, female head, minority, year 2012, and year 2014. Full results (including for controls) presented in table A.6.

Source: Authors' calculation based on socio-economic data from VHLSS 2010, 2012 and 2014 and environmental data from Hansen *et al.*, 2013; Vu *et al.*, 2014b; Brauer *et al.*, 2015, Harmonized World Soil Database, Climate Research Unit, Bangalore *et al.*, 2016, and Winsemius *et al.*, 2015.

2012–14'). Among poor households, those living in communes with higher rainfall variability and drought hazards have a significantly lower consumption growth (table 2, column 'Poor'), which is an alarming result suggesting that increasing rainfall variability and recurring droughts mainly have negative impacts on those that are already in a destitute situation.

Some interesting findings also appear from the results for the control variables (full results presented in tables A.5 and A.6). Higher levels of current rainfall and lower current temperatures are related to higher consumption levels and growth over time, which is broadly in line with the results in Narloch (2016).[17] While larger distance to cities and roads relates to lower consumption levels as would be expected, it is related to higher consumption growth over time – possibly indicating a catching-up of more remote communes. Having access to larger agricultural and water surface areas has a positive effect on both consumption levels and growth over time. Ethnic minorities have lower consumption levels and also experience lower consumption growth when compared to wealthier households. However, within the sub-samples of households below the poverty line and in the lowest two consumption quintiles, ethnic minorities have higher consumption growth.

These results should be interpreted with some caution. First, based on the available data, omitted variable bias is minimized but not eliminated. As some of the findings suggest, there may be some incidences in which being located in a high risk zone can also indicate other factors that explain living standards but cannot be controlled for with the available data. Furthermore, it should be highlighted that some of the differences between the results from the *Pooled* and the *Panel* could be due to the different subsamples of households included in these analyses.

8. Conclusions

Despite several limitations related to the available data sets, this study provides important insights into the multi-faceted relationship between poverty and environmental risks based on the combination of high-resolution, geo-spatial data and household data from Vietnam. By using consistent data and methods within the same country, we can shed some light on how the relationship between poverty and multiple dimensions of environmental risk varies as a function of the channels through which poverty and risk interact. The findings highlight the fact that indeed the relationship is hard to generalize, as it depends on the specific types of risks, scale of analysis and locations of interest, and could possibly be driven by different causal linkages.

The main results regarding the four research questions are: (i) at the district level, the incidence of poverty is higher in high risk areas, (ii) similarly, at the household level, poorer households face higher environmental risks, (iii) for some risks, their relationship with household-level consumption varies between rural and urban areas, and (iv) environmental risks explain consumption differences between households, but less so consumption changes over time. In particular, lower household consumption levels are related to steeper slopes, higher rainfall variability and drought hazards in rural communes and higher flood hazards in urban communes. Consumption growth is lower for households in communes with higher air pollution. And for poor households, higher rainfall variability and drought hazards relate to lower consumption growth, implying

---

[17]Some of the results in Narloch (2016) differ as the analyses reduce omitted variable biases through fixed effects regressions.

the existence of poverty traps as relates to weather risks. Although the data do not allow us to conclude that environmental risks generally result in lower consumption growth, these findings suggest that poor people are disproportionally exposed to environmental risks.

More work is needed to confirm the potentially causal relationships between environmental risks and poverty. First, longer time-series data is needed to evaluate whether environmental conditions have long-lasting impacts on household living standards. Second, this study mostly relies on global datasets from remote sensing or modeling work, which need to be verified and refined with monitored data at the sub-national level – optimally from ground stations. Moreover, this study could only define historic risk profiles and not the actual environmental conditions and risk materialization within the survey years. The expansion of these analyses with such data will be an important area for deepening the findings of this work. Furthermore, alternative approaches could be applied to estimate causal impacts: for instance, to estimate deforestation-poverty linkages, future work may use discontinuities provided by borders (either at the sub-national or national level as in Crespo Cuaresma *et al.*, 2017) or use instrumental variables such as temperature inversions (which have been used as an instrument for pollution levels as in Sager, 2016).

Even in the absence of such analyses, some evidence already exists that shows the detrimental impacts of environmental risks on poverty and household welfare. An accompanying study, for example, shows that actual variation in rainfall and temperature conditions in rural areas is related to significant consumption and income effects also for poor people (Narloch, 2016). In addition, other work has shown the negative welfare and poverty impacts of flood and drought events (Thomas *et al.*, 2010; Bui *et al.*, 2014; Arouri *et al.*, 2015). Moreover, poor people could be affected by environmental risks in many ways that go beyond income and consumption effects, such as detrimental health impacts or a decline in the quality of life due to poor environmental conditions. Such impacts cannot be measured with the available household data.

Altogether, the findings provide important insights into the relevance of poverty reduction policies under climate change. The disproportionate exposure of poor people to multiple environmental risks suggests that these people are more vulnerable to climate shocks. At the same time, climate change is likely to increase some of these risks, thus exacerbating already existing poverty traps. Strategies to reduce poverty – especially in rural areas – need to address environmental risks and climate change simultaneously. For example, ecosystem-based adaptation could strengthen ecosystem resilience to climate change and reduce environmental risks, while improving the livelihoods of people depending on these ecosystems. Carefully designed land-use planning policies, paired with investments in livelihood support and improved mobility that encourage resettlements and avoid new settlements in high risk areas, are another strategy to reduce exposure to environmental risks and climate shocks, while reducing human pressure on already fragile ecosystems. Generally, addressing environmental risks deserves greater attention in poverty reduction policies – especially in the face of climate change.

References

Akter S and Mallick A (2013) The poverty-vulnerability-resilience nexus: evidence from Bangladesh. *Ecological Economics* **96**, 114–124.

Angelsen A, *et al.* (2014) Environmental income and rural livelihoods: a global-comparative analysis. *World Development, Forests, Livelihoods, and Conservation* **64**(suppl. 1), S12–S28.

Arouri M, Nguyen C and Youssef AB (2015) Natural disasters, household welfare, and resilience: evidence from rural Vietnam. *World Development* **70**, 59–77.

Baggio JA and Papyrakis E (2010) Ethnic diversity, property rights, and natural resources. *The Developing Economies* **48**(3), 473–495.

Bandyopadhyay S and Skoufias E (2015) Rainfall variability, occupational choice, and welfare in rural Bangladesh. *Review of Economics of the Household* **13**(2), 589–634.

Bandyopadhyay S, Shyamsundar P and Baccini A (2011) Forests, biomass use and poverty in Malawi. *Ecological Economics* **70**(12), 2461–2471.

Bangalore M, Smith A and Veldkamp T (2016) *Exposure to Floods, Climate Change, and Poverty in Vietnam*. World Bank Policy Research Working Paper Series No. 7765, Washington, DC: World Bank.

Barbier EB (2010) Poverty, development, and environment. *Environment and Development Economics* **15**, 635–660.

Barbier EB (2012) *Natural Capital, Ecological Scarcity and Rural Poverty*. World Bank Policy Research Working Paper Series No. 6232, Washington, DC: World Bank.

Barbier EB (2015) *Climate Change Impacts on Rural Poverty in low-Elevation Coastal Zones*. World Bank Policy Research Working Paper Series No. 7475, Washington, DC: World Bank.

Barrett CB, Travis AJ and Dasgupta P (2011) On biodiversity conservation and poverty traps. *Proceedings of the National Academy of Sciences* **108**, 13907–13912.

Barrios S, Bertinelli L and Strobl E (2010) Trends in rainfall and economic growth in Africa: a neglected cause of the African growth tragedy. *The Review of Economics and Statistics* **92**(1), 350–366.

Braubach M and Fairburn J (2010) Social inequities in environmental risks associated with housing and residential location – a review of evidence. *European Journal of Public Health* **20**(1), 36–42.

Brauer M, *et al.* (2015) Ambient air pollution exposure estimation for the global burden of disease 2013. *Environment Science and Technology* **50**(1), 79–88.

Bui AT, *et al.* (2014) The impact of natural disasters on household income, expenditure, poverty and inequality: evidence from Vietnam. *Applied Economics* **46**, 1751–1766.

Carter MR, *et al.* (2007) Poverty traps and natural disasters in Ethiopia and Honduras. *World Development* **35**, 835–856.

Chomitz KM, *et al.* (2007) *At Loggerheads: Agricultural Expansion, Poverty Reduction, and Environment in the Tropical Forests*. Washington, DC: World Bank.

Crespo Cuaresma JC, *et al.* (2017) Economic development and forest cover: evidence from satellite data. *Scientific Reports* **7**, 40678.

Dasgupta S, *et al.* (2005) Where is the poverty–environment nexus? Evidence from Cambodia, Lao PDR, and Vietnam. *World Development* **33**, 617–638.

del Ninno C, *et al.* (2001) *The 1998 Floods in Bangladesh: Disaster Impacts, Household Coping Strategies, and Response*. Research Report No. 122, International Food Policy Research Institute, Washington, DC.

Duraiappah AK (1998) Poverty and environmental degradation: a review and analysis of the nexus. *World Development* **26**(12), 2169–2179.

Ebenstein A, *et al.* (2015) Growth, pollution, and life expectancy: China from 1991–2012. *The American Economic Review* **105**(5), 226–231.

Fay M (2005) *The Urban Poor in Latin America*. Washington, DC: World Bank.

Forouzanfar MH, *et al.* (2015) Global, regional, and national comparative risk assessment of 79 behavioural, environmental and occupational, and metabolic risks or clusters of risks in 188 countries, 1990–2013: a systematic analysis for the global burden of disease study 2013. *The Lancet* **386**, 2287–2323.

Fox S (2014) The political economy of slums: theory and evidence from Sub-saharan Africa. *World Development* **54**, 191–203.

Geographic Information Science and Technology (2015) *Landscan Population Data*, Oak Ridge, USA: Oak Ridge National Laboratory.

Gerber N, Nkonya E and von Braun J (2014) Land degradation, poverty and marginality. In von Braun J and Gatzweiler FW (eds). *Marginality*. Dordrecht, The Netherlands: Springer, pp. 181–202.

Gordon SB, *et al.* (2014) Respiratory risks from household air pollution in low and middle income countries. *The Lancet Respiratory Medicine* **2**(10), 823–860.

Grainger CA and Costello CJ (2014) Capitalizing property rights insecurity in natural resource assets. *Journal of Environmental Economics and Management* **67**(1), 224–240.

Gray LC and Moseley WG (2005) A geographical perspective on poverty–environment interactions. *The Geographical Journal* **171**, 9–23.

Hallegatte S, *et al.* (2016) *Shock Waves: Managing the Impacts of Climate Change on Poverty*. Climate Change and Development Series, Washington, DC: World Bank.

Hallegatte S, *et al.* (2017) *Unbreakable: Building the Resilience of the Poor in the Face of Natural Disasters*. Climate Change and Development Series, Washington, DC: World Bank.

Hansen MC, *et al.* (2013) High-resolution global maps of 21st-century forest cover change. *Science* **342**, 850–853.

Harris I, *et al.* (2014) Updated high-resolution grids of monthly climatic observations – the CRU TS3.10 dataset. *International Journal of Climatology* **34**, 623–642.

ISM and SINFONICA (2015) *Users' Manual for Handling Resampled Micro Data of Vietnamese Household Living Standard Survey (VHLSS)*. Tokyo, Japan: Institute of Statistical Mathematics (ISM) and Statistical Information Institute for Consulting and Analysis (SINFONICA).

Khan RK and Khan RK (2009) Assessing poverty-deforestation links: evidence from swat, Pakistan. *World Development* **68**, 2607–2618.

Kozel V (2014) *Well Begun but Not Yet Done: Progress and Emerging Challenges for Poverty Reduction in Vietnam*. Washington, DC: World Bank.

Lall SV and Deichmann U (2012) Density and disasters: economics of urban hazard risk. *The World Bank Research Observer* **27**(1), 74–105.

Lanjouw P, Marra M and Nguyen C (2013) *Vietnam's Evolving Poverty map: Patterns and Implications for Policy*. World Bank Policy Research Working Paper Series No. 6355, Washington, DC: World Bank.

Laurance WF, Sayer J and Cassman KG (2014) Agricultural expansion and its impacts on tropical nature. *Trends in Ecology & Evolution* **29**(1), 107–116.

Li Y, *et al.* (2013) Rural livelihoods and climate variability in ningxia, northwest China. *Climatic Change* **119**(3–4), 891–904.

Locatelli B, Pramova E and Russell A (2012) *Using Forests to Enhance Resilience: What do we Know About how Forests can Contribute to Adaptation?* Washington, DC: World Bank.

Luong LM, *et al.* (2017) The association between particulate air pollution and respiratory admissions among young children in Hanoi, Vietnam. *Science of the Total Environment* **578**, 249–255.

Naipal V, *et al.* (2015) Improving the global applicability of the RUSLE model-adjustment of the topographical and rainfall erosivity factors. *Geoscientific Model Development* **8**, 2893–2913.

Narloch U (2016) *The Varying Income Effects of Weather Variation: Some Insights From Rural Vietnam*. World Bank Policy Research Working Paper Series No. 7764, Washington, DC: World Bank.

Narloch U and Bangalore M (2016) *Environmental Risks and Poverty: Analyzing geo-Spatial and Household Data From Vietnam*. World Bank Policy Research Working Paper Series No. 7763, Washington, DC: World Bank.

Noack F, *et al.* (2015) *Responses to Weather and Climate: A Cross-Section Analysis of Rural Incomes*. World Bank Policy Research Working Series No. 7478, Washington, DC: World Bank.

Nunn, N and Puga D (2012) Ruggedness: the blessing of bad geography in Africa. *Review of Economics and Statistics* **94**(1), 20–36.

Olinto P, *et al.* (2013) The state of the poor: where are the poor, where is extreme poverty harder to end, and what is the current profile of the world's poor? *Economic Premise*, **2**(125), 1–8. World Bank, Washington, DC.

Opondo DO (2013) Erosive coping after the 2011 floods in Kenya. *International Journal of Global Warming* **5**, 452–466.

Panayotou T (1997) Demystifying the environmental Kuznets curve: turning a black box into a policy tool. *Environment and Development Economic* **2**(3), 465–484.

Panayotou T (2016) Economic growth and the environment. In Haen N, Wilk R and Harnish A (eds). *The Environment in Anthropology*, 2nd edn., New York: NYU Press, pp. 140–148.

Pasanen T, *et al.* (2017) Poverty–environment nexus in the Lao PDR: analysis of household survey data. *Development Policy Review* **35**(2), 349–371.

Perez-De-Rada E and Paz D (2008) *Analisis de la Relacion entre Amenazas Naturales y Condiciones de Vida: El Caso de Bolivia*. Research Report, United Nations Development Programme, New York City, USA.

Petley D (2010) On the impact of climate change and population growth on the occurrence of fatal landslides in South, East and SE Asia. *Quarterly Journal of Engineering Geology and Hydrogeology* **43**, 487–496.

Petley D (2012) Global patterns of loss of life from landslides. *Geology* **40**, 927–930.

Pham TT, *et al.* (2012) *The Context of REDD + in Vietnam: Drivers, Agents and Institutions*. Occasional Paper 75, Bogor, Indonesia: Center for International Forestry Research (CIFOR).

Rabbani G, Rahman A and Mainuddin K (2013) Salinity-induced loss and damage to farming households in coastal Bangladesh. *International Journal of Global Warming* **5**(3), 400–415.

Ranger N, *et al.* (2011) An assessment of the potential impact of climate change on flood risk in Mumbai. *Climatic Change* **104**(1), 139–167.

Reardon T and Vosti SA (1995) Links between rural poverty and the environment in developing countries: asset categories and investment poverty. *World Development* **23**, 1495–1506.

Sager L (2016) *Estimating the Effect of air Pollution on Road Safety Using Atmospheric Temperature Inversions*. Grantham Research Institute on Climate Change and the Environment, Working paper no. 251. London, UK.

Scherr S (2000) A downward spiral? Research evidence on the relationship between poverty and natural resource degradation. *Food Policy* **25**, 479–498.

Sidle RC, *et al.* (2006) Erosion processes in steep terrain – truths, myths, and uncertainties related to forest management in Southeast Asia. *Forest Ecology and Management* **224**, 199–225.

Sietz D, Choque SEM and Lüdeke MK (2012) Typical patterns of smallholder vulnerability to weather extremes with regard to food security in the Peruvian Altiplano. *Regional Environmental Change* **12**(2), 489–505.

Sissoko K, van Keulen H, Verhagen J, Tekken V and Battaglini A (2011) Agriculture, livelihoods and climate change in the West African Sahel. *Regional Environmental Change* **11**(1), 119–125.

Sloan S and Sayer JA (2015) Forest resources assessment of 2015 shows positive global trends but forest loss and degradation persist in poor tropical countries. *Forest Ecology and Management*, **352**, 134–145.

Sodhi NS, *et al.* (2010) Conserving Southeast Asian forest biodiversity in human-modified landscapes. *Biological Conservation* **143**, 2375–2384.

Stern DI (2004) The rise and fall of the environmental Kuznets curve. World Development **32**(8), 1419–1439.

Tansley G, *et al.* (2017) The correlation between poverty and access to essential surgical care in Ghana: a geospatial analysis. *World Journal of Surgery* **41**(2), 639–643.

Thomas T, *et al.* (2010) *Natural Disasters and Household Welfare: Evidence From Vietnam*. World Bank Policy Research Working Paper Series No. 5491, Washington, DC: World Bank.

Tschakert P (2007) Views from the vulnerable: understanding climatic and other stressors in the Sahel. *Global Environmental Change* **17**(2), 381–396.

Tucker J, *et al.* (2015) Social vulnerability in three high-poverty climate change hot spots: what does the climate change literature tell us. *Regional Environmental Change* **15**(5), 783–800.

Vezina K, Bonn F and Van CP (2006) Agricultural land-use patterns and soil erosion vulnerability of watershed units in Vietnam's northern highlands. *Landscape Ecology* **21**, 1311–1325.

Von Braun J, et al. (2013) *The Economics of Land Degradation*. ZEF Working Paper No. 109. Bonn, Germany: Center for Development Research.

Vu QM, et al. (2014a) Socio-economic and biophysical determinants of land degradation in Vietnam: an integrated causal analysis at the national level. *Land Use Policy* **36**, 605–617.

Vu QM, Le QB and Vlek PL (2014b) Hotspots of human-induced biomass productivity decline and their social–ecological types toward supporting national policy and local studies on combating land degradation. *Global Planetary Change* **121**, 64–77.

Watmough GR, et al. (2016) Understanding the evidence base for poverty-environment relationships using remotely sensed satellite data: an example from Assam, India. *World Development* **78**, 188–2013.

Winsemius H, et al. (2015) *Disaster Risk, Climate Change, and Poverty: Assessing the Global Exposure of Poor People to Floods and Droughts*. World Bank Policy Research Working Paper Series No. 7480, Washington, DC: World Bank.

Wodon Q, Liverani A and Joseph G (2014) *Climate Change and Migration: Evidence From the Middle East and North Africa*. Washington, DC: A World Bank study.

World Bank Group (2016) *Vietnam – Systematic Country Diagnostic: Priorities for Poverty Reduction, Shared Prosperity and Sustainability*. Washington, DC: World Bank.

Wunder S, et al. (2014) Safety nets, gap filling and forests: a global-comparative perspective. *World Development, Forests, Livelihoods, and Conservation* **64**(suppl. 1), S29–S42.

Zimmerman FJ and Carter MR (2003) Asset smoothing, consumption smoothing and the reproduction of inequality under risk and subsistence constraints. *Journal of Development Economics* **71**(1), 233–260.

Zulu LC and Richardson RB (2013) Charcoal, livelihoods, and poverty reduction: evidence from sub-Saharan Africa. *Energy for Sustainable Development* **17**(1), 127–137.