**RESEARCH**

# The Impacts of Multiple Tropical Cyclone Events and Associated Precipitation on Household Income and Expenditures

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**Abstract**

Tropical cyclones (TCs) are one of the most destructive natural hazards. Damages arise from strong winds, compounded by associated flood-inducing hazards such as heavy rainfall and storm surge. Recent papers have shown that the modelled TC damage estimates fall short of the observed estimates due to the use of wind speed as a sole damage proxy. Damage estimates may be further confounded by inaccurate representations of vulnerability of people and economic sectors, for example, calling for adjusted damage thresholds in less developed regions. This paper evaluates the impacts of compounded TC hazards on household income and expenditure in the Philippines, with adjustments in vulnerability representation drawn from local information. Our results show that the omission of TC-associated precipitation leads to an underestimation of impacts, as well as the number of areas and economic sectors affected by TCs. We find that households cope through a reallocation of budgets and reliance on alternative income sources. Despite extensive public and private disaster risk reduction and management strategies, we still find significant losses in income and expenditures at any number of TC exposure.

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## Introduction

Tropical cyclones (TCs) are one of the most destructive natural hazards. Due to its multi-hazardous and repetitive nature, and the heterogeneity in exposed households, quantifying the effects of TCs is complex and challenging. In this study, we account for multiple TC-associated hazards (i.e., wind intensity and precipitation) that occur frequently within a year, as well as local realities in adjusting the vulnerability thresholds of the wind damage index to estimate TC impacts on households in the Philippines. We further test for adaptation using two specific household groups: households that are repeatedly exposed to extreme magnitudes of TCs (or those that are likely to adapt) and food-poor households (or those that have limited capacity to adapt).

Each year, TCs cause disastrous damages to communities in various parts of the world, with adverse economic consequences that can extend over many years. Direct and immediate damages to property and human health caused by TCs can be exacerbated by indirect and delayed impacts. These include the disruption in supply-chain networks resulting in loss of jobs, income and economic growth. The destruction of critical infrastructure (e.g., power transmission lines, sanitary facilities, healthcare and educational facilities, roads, water pipes) prevents public access to basic utilities (e.g., healthcare, education, food supply, potable water), and can have long-term consequences for individuals' well-being (Lenzen et al. 2019; Kunze 2021; PAGASA 2023; Krichene et al. 2021). Additionally, the accumulation of stagnant rainwater and debris becomes a breeding ground for mosquitoes, leading to higher risk of dengue and other vector-borne diseases.

The Philippines is one of the countries that are highly exposed to multiple TCs, among many natural disasters. It records an average of eight to nine TCs making landfall annually (Cinco et al. 2016; PAGASA 2023), and is ranked as the fourth most climate-affected country in the world based on the long-term climate index, due to recurring, destructive TCs (Eckstein et al. 2021). Within the years 2004-2015 covered by this study, 73 TCs have made landfall in the Philippines; of which three are category 5 TCs[1], eight are category 4 TCs[2], and seven are category 3 TCs [3]. Other TCs with wind intensity below category 1 during this period were still highly destructive due to associated rainfall [4] (UN OCHA 2017). From 1948-2010, a decreasing trend in the frequency of TCs making landfall was observed, however, nine out of the ten most destructive TCs during this period occurred between 1991 and 2010 (Lee et al. 2012), and 80 percent of the damages and deaths were caused by only six TCs between 1970 and 2014 (Espada 2018).

Because TCs predominantly occur in the second half of the year, many households, particularly those in the northeastern regions, are exposed to multiple TCs in close succession.[5] TCs can also coincide with the build-up of the southwest monsoon around the months May

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[1] Haiyan in 2013, Bopha in 2012, Megi in 2010.

[2] Noul, Melor, Koppu in 2015, Utor in 2013, Nalgae in 2011, Xangsane, Durian, Cimaron in 2006.

[3] Rammasun and Hagupit in 2014, Nari in 2013, Nesat and Nanmadol in 2011, Utor and Chebi in 2006.

[4] Ketsana and Parma in 2009, and Fengshen in 2008.

[5] E.g., Tropical Storm Ketsana (local name: Ondoy) and Typhoon Parma (local name: Pepeng) in late September and early October 2009. The two storms resulted in total damages of USD 852 million (UN OCHA 2017), and a total cost of recovery and reconstruction of USD 4.4 billion (GFDRR 2009)

to September, which can result in heavier precipitation over a very short time period.[6] Due to high levels of precipitation, disaster records show massive damages, even for TCs with weak wind speeds. An example of this is Tropical Storm Ketsana (local name: Ondoy) in 2009 that had wind speeds of only 46kn (85 kph) at the center and gusts up to 65kn (120 kph)[7], but has brought in a maximum of 455 mm of rain within 24 hours[8], which resulted in a sudden, six-meter-high flood in parts of Metro Manila (UN OCHA 2009b; GFDRR 2009; UN OCHA 2009a). It had a total estimated damage of USD 244 million.

Recent evidence shows that future exposure to TCs and associated hazards will continue to rise in the Philippines due to further intensification of TCs under climate change and demographic development (Geiger et al. 2021). Annual expected damages[9] are estimated to increase by 7.2 percent in 2050 relative to 2015 (Eberenz et al. 2021), necessitating a better understanding of households' responses and vulnerabilities.

At the household level, TCs lead to a significant reduction in welfare, corresponding to a reduction in income and expenditures (Henry et al. 2020; Arouri et al. 2015; Baez et al. 2017; Ishizawa and Miranda 2019; Baez and Santos 2007). Using household data from 1985-2006, Anttila-Hughes and Hsiang (2013) estimated the average reduction in income and expenditures of households in the Philippines of 6.6% and 7.1%, respectively, and found that TCs lead to reduced expenditures on human capital investment including health and education. Using household data from 2003-2015, Skoufias et al. (2020) estimated the effect of wind from TCs on per capita expenditure in the Philippines of about -11.4 percent[10], and found that education and medical expenditures are unaffected by TCs. Deuchert and Felfe (2015) found negative and persistent effects of TC Mike in 1990 in Cebu City on children's education but no effects on children's health. No significant statistical impacts, however, do not always signify no effect in reality. For instance, these findings are justified by the local behaviour in dealing with health conditions, wherein the default and initial response of Filipinos is to endure illnesses rather than to resort to other means of covering health expenses such as borrowing[11], begging, or the reliance on insurance (Lasco et al. 2022). That is, people are affected, but these are not always reflected in objective indicators, such as expenditure levels.

The impacts of TCs are also disproportionately distributed among households, where the poor have a relatively higher risk (Anttila-Hughes and Hsiang 2013; Walsh et al. 2020; Sakai et al. 2017; Yonson et al. 2018; Deuchert and Felfe 2015). The poor are more often exposed to hazards due to the location of their houses (i.e., housing costs tend to be lower where risks are higher) (Hallegatte et al. 2020, 2015). They are also more vulnerable than non-poor households, because the ratio of the value of damaged property to the total value of their assets is relatively higher, they are more likely to be engaged in resource-dependent

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[6] E.g., Typhoon Fengshen (local name: Frank) in 2008 and Typhoon Morakot (local name: Kiko) in 2009 (Villarin et al. 2016)

[7] These wind speeds are just below the Saffir-Simpson scale category 1 storm level.

[8] Estimated by Sato and Nakasu 2011 to have a return period of 1 in 100 years over a 24-hour period or 1 in 150 years over a 12-hour period.

[9] Assuming a "current policies" scenario, where there are no further changes to implemented mitigation action in 2020, and will lead to an estimated global warming of 2.5-2.9°C by 2100. This scenario is based on the Climate Action Tracker https://climateactiontracker.org/. Projections based on CLIMADA were accessed through the Climate Impact Explorer https://climate-impact-explorer.climateanalytics.org/ on December 12, 2023.

[10] Given a wind index value of 0.729 at the historical maximum wind speed between 1950 and 2016.

[11] including informal borrowing which impose high interest rates and short repayment schemes.

livelihoods, and they have less resources to rebuild and recover what was destroyed (UNDRR 2022; Hallegatte et al. 2015). In particular, food-poor households, or those whose income is insufficient to cover basic nutritional needs, do not have enough financial buffer to face unexpected expenses, and are, therefore, at risk of having long-term and inter-generational effects on overall well-being (Perez-Escamilla and Moran 2023). In the Philippines, the financial status of ill persons discourages them to seek professional health care until the illness is already unbearable, leading to catastrophic illnesses or illnesses that require more than 40 percent of effective income for health expenditures; which could have otherwise been prevented with early treatment (Lasco et al. 2022).

On the other hand, the repeated occurrence or the anticipation of future occurrences of TCs encourages adaptation action to mitigate damages and seize opportunities for positive changes (e.g., build-back-better wherein a negative impact is responded to by a growth-inducing stimulus that increases productivity and resilience, and an increase in financial inflows (Chhibber and Laajaj 2008)). In the Philippines, multiple TC exposure has led to several initiatives by the government and private households.

For over 50 years, the Philippines has been adopting and implementing disaster risk reduction (DRR) strategies and engaging in international cooperation to strengthen disaster support[12] in order to mitigate and minimise TC impacts. Funding for the disaster-related programs is ensured through local funding, on top of international support. For instance, local government units (LGUs) are mandated to set aside 5% of revenue for their disaster councils, and 70% of local Disaster Risk Reduction and Management (DRRM) funds should be used for pre-disaster activities, while the rest are to be allocated for recovery and relief programs (Quick Response Fund) (Rey 2015).[13].

Through the legal frameworks and funding sources, the government is able to provide anticipatory measures to mitigate the impacts of disasters, as well as post-disaster responses such as employment and cash support for those that are affected and to provide food security measures to minimise agricultural impacts. One of the mandates of the Philippine Atmospheric, Geophysical and Astronomical Services Administration (PAGASA) is to provide sufficient, up-to-date and timely information on weather-related events to help the government and the people prepare for calamities. Their services include forecasting and early warning signals, monitoring during a natural disaster, and post-disaster evaluation. For instance, PAGASA's TC advisory includes forecasts on wind, storm surge, and associated precipitation. Using the early warnings from PAGASA, the Philippine government issues the necessary precautionary measures, including calling off classes and office work in order for people to remain in their homes, or directing possibly affected population to evacuation centers. Other government agencies, such as the Department of Agriculture (DA) and the Department of Environment and Natural Resources (DENR) also issue warnings to consumers on possibly toxic food due to the after-effects of a TC, and restrictions to economic activity of workers who are directly exposed to natural hazards.

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[12] Examples of these are the Hyogo Framework for Action (HFA) in 2005, ratification of the Agreement on Disaster Management and Emergency Response (AADMER) within the Association of Southeast Asian Nations (ASEAN) in 2009, and the Philippine Disaster Risk Reduction and Management Act (Congress of the Philippines 2010) of 2010 (RA No. 10121).

[13] Other formalised funding are the General Appropriations Act (GAA), National and Local Disaster Risk Reduction and Management Fund (NDRRMF) and LDRRMF, respectively), Priority Development Assistance Fund (PDAF), Adaptation and Risk Financing, Disaster Management Assistance Fund (DMAF), Peoples Survival Fund (PSF), and other donor funding sources (Office of the Civil Defense 2011; Rey 2015).

Post-disaster responses include the Department of Labor and Employment (DOLE)'s Integrated Livelihood and Emergency Employment Program (DILEEP), which links disaster and climate risk management with social security and active labor market policies; and the Department of Social Welfare and Development (DSWD)'s shelter assistance, cash transfer programs, and food and non-food items relief distribution. The DA ensures price stability of staple crops, for instance, by having buffer stocks to be released during times of supply shortages, as well as seed programs for fast replanting and regrowing to recover the income lost from damaged crops.

From a private capacity, Maquiling et al. (2021) show that households are more likely to cooperate and follow early warning signals and understand what the signals mean, based on prior experience. They also invest more in flood-proofing their assets, e.g, raising the level of the flooring of one's house corresponding to the level of water experienced during previous flooding, and replacing wood furniture with plastic (Maquiling et al. 2021).

The combination of TC-associated hazards can potentially inflict larger damages due to its potential to cause flooding, erosion, salinisation of vegetation and destruction of physical infrastructure (Kunze 2021; Anttila-Hughes and Hsiang 2013; Bakkensen et al. 2018; Baldwin et al. 2023; Kure et al. 2016; Wahl et al. 2015). Knutson et al. (2020) provide projections on TC activity given future levels of global warming and show that, globally, average TC wind speeds and TC-associated precipitation rates are likely going to increase. Recent studies also argue that the amount of rainfall is a significant factor in determining losses from TCs (Bakkensen et al. 2018; Collalti and Strobl 2022). Baldwin et al. (2023) have shown that even upon adjusting the specification of the scaled wind damage index to reflect regional vulnerability, the modelled impact estimates still show zero damages for some storms that recorded actual damages; and hypothesise that this may be due to the omission of associated hazards such as precipitation.

In assessing TC impacts, local realities need to be taken into consideration to arrive at the appropriate vulnerability factor. For instance, a scaled wind damage index introduced by Emanuel (2011) and used by several succeeding publications on TCs in the Philippines (Skoufias et al. 2020; Strobl 2019; Baldwin et al. 2023) incorporates both the magnitude of wind and vulnerability, or the susceptibility of areas and persons to be adversely affected. However, vulnerability representations in wind-related damages have relied only very lightly, if at all, on local information and experiences. Furthermore, the macroeconomic nature of global studies on TCs also fail to provide information on the heterogeneity of impact on individual households, wherein the additional impact of precipitation has not been well quantified.

Using the Philippines as a case study, we contribute to the ongoing development in TC impact modelling by incorporating local knowledge to adjust the damage function for wind-related damages, and by explicitly accounting for both wind and TC-associated precipitation. We quantify the impacts of compound TCs on household income and expenditure, and evaluate the heterogeneity in impacts among different income sectors and food and non-food expenditure groups, as well as different likelihoods of adaptation among households. We revert back to documented local practices and implemented disaster risk reduction policies in discussing our results.

By means of fixed effects regression, we identify the impact of multiple exposure to TC wind and associated precipitation on Philippine households by exploiting within-municipality year-to-year variation. We employ climate datasets characterized by high resolution and frequency: TCE-DAT (Geiger et al. 2018) on TC wind speed data, and the Global Precipitation

Climatology Centre (GPCC) on precipitation data. A wind damage index is calculated based on the wind speed data and an adjusted damage function that draws from local precautionary measures based on early warning signals from PAGASA. These are combined with the repeated cross-sectional, nationally representative Family Income and Expenditure Survey (FIES).

## Data

The data used in this study cover the years 2004-2015. Within these years, we are able to use four FIES, which are conducted every three years, and climate variables that are temporally aggregated to an annual level for 12 years. In this section, we will discuss in detail our data sources, variables used, as well as the transformation of variables conducted.

### Household Data

The FIES is a nationwide household survey conducted triennially by the Philippine Statistics Authority (PSA). Initiated in 1985, this survey provides crucial insights into the economic dynamics of households in the Philippines. Each final survey data set comprises averaged responses collected from two waves that interview the same households within a survey year. The first wave is conducted in July of the given year to collect information from January to June, while the second wave is conducted in January of the following year to collect data from July to December.

The inclusion of the responses of households to the final survey report requires that the households respond to both waves of the survey year. That is, households that have only completed one of the two survey rounds are excluded from the final survey report. This may be due to households not being physically present during the visit (either temporarily or permanently), their refusal to be interviewed, or the destruction of housing units by a disaster such as a typhoon or fire (Philippine Statistics Authority 2015). The total response rate for the final surveys we have used in this study are above 90 percent.

The FIES provides information on the location of the household at the barangay level[14]. However, due to the frequent changes in the area covered by and the naming of the *barangays*, we have opted to refer to the location of the households by their municipality[15].

The selection of household respondents for any FIES wave automatically excludes those that are located in one of the Least Accessible *Barangays* (LABs). A *barangay* is classified as a LAB if it meets at least one of three criteria: (1) the trip requires more than eight hours of walking from the last vehicle station, (2) transportation services are available less than three times a week, or (3) a one-way trip costs more than 500 Philippine Pesos (roughly USD 9). A total of 350 LABs were identified by the PSA, which make up 0.83 percent of the total number of *barangays*.

Having enumerated these exclusions, the final survey reports in relation to our analysis of the impacts of an extreme weather event may be attenuated due to three reasons: (1) the averaging of the responses from two survey waves, (2) the exclusion of households that are most geographically disconnected, and (3) the exclusion of households that have lost their homes due to TCs before both survey waves are completed. For reasons (1) and (3),

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[14] A *barangay* is the smallest administrative unit in the Philippines (administrative level 4).

[15] The municipality level refers to administrative level 3. Administrative level 1 classify the area into the 17 regions, and level 2 into provinces.

it is important to note that the majority of TCs happen in the second half of the year, and will likely have a larger effect on the 2nd wave of the FIES; while reason (2) excludes a household group that, when exposed to TCs, is highly vulnerable to impacts, given their limited physical access to social and economic support (e.g., emergency response and relief). For these reasons, we expect our econometric results to be lower bound estimates of TC impacts.

In our analysis, we focus on the impacts of TCs on two major groups of dependent variables sourced from the FIES: expenditures and income. Descriptive statistics of both categories are displayed in Table 1.

The PSA calculates the total household expenditures in the FIES using a bottom-up approach of all the expenditure categories: total non-food expenses (i.e., housing, health,

**Table 1** Descriptive statistics of FIES data used as dependent variables. Note: All expenditure items are per adult equivalent based on the modified OECD weights

| Variable | 2006 | | 2009 | | 2012 | | 2015 | |
|---|---|---|---|---|---|---|---|---|
| | Mean | St. Dev. | Mean | St. Dev. | Mean | St. Dev. | Mean | St. Dev. |
| Total income | 56,366 | 59,263 | 59,141 | 63,745 | 57,603 | 58,453 | 59,513 | 59,215 |
| Total adjusted income | 23,14 | 13,926 | 23,309 | 13,593 | 23,387 | 13,659 | 22,851 | 13,162 |
| Crops | 33,226 | 48,59 | 35,832 | 53,41 | 34,216 | 47,943 | 36,662 | 49,793 |
| Livestock and poultry | 6,19 | 1,975 | 6,166 | 1,961 | 6,267 | 2,162 | 5,968 | 2,639 |
| Fisheries | 3,347 | 3,46 | 3,268 | 3,291 | 3,305 | 3,303 | 3,124 | 2,953 |
| Forestry | 2,934 | 1,878 | 2,918 | 1,865 | 2,872 | 1,942 | 2,618 | 1,817 |
| Trade | 1,68 | 2,382 | 1,677 | 2,411 | 1,591 | 2,212 | 1,605 | 2,252 |
| Manufacturing | 2,501 | 1,844 | 2,455 | 1,721 | 2,092 | 1,475 | 1,888 | 1,325 |
| Community services | 1,717 | 10,233 | 1,805 | 9,376 | 2,185 | 9,427 | 2,294 | 9,412 |
| Transport | 2,269 | 7,192 | 2,249 | 6,975 | 2,103 | 6,435 | 1,9 | 5,852 |
| Mining and quarrying | 281 | 1,828 | 280 | 1,182 | 944 | 3,27 | 576 | 2,126 |
| Construction | 12,117 | 19,19 | 13,13 | 22,711 | 12,356 | 17,88 | 12,992 | 20,02 |
| Entrepreneurial activities | 1,36 | 2,154 | 1,363 | 1,966 | 1,5 | 2,255 | 1,549 | 2,334 |
| Cash from abroad | 409 | 822 | 425 | 806 | 376 | 770 | 253 | 556 |
| Cash from domestic | 524 | 859 | 504 | 797 | 493 | 869 | 519 | 956 |
| Total expenditure | 163,528 | 201,747 | 168,38 | 251,76 | 166,474 | 196,612 | 173,35 | 203,784 |
| Non-food expenditure | 140,283 | 180,323 | 143,574 | 237,173 | 141,004 | 181,524 | 147,587 | 192,4 |
| Housing | 10,782 | 29,851 | 11,593 | 39,381 | 9,635 | 30,683 | 9,391 | 32,532 |
| Health | 1,488 | 9,874 | 1,265 | 10,2 | 965 | 9,312 | 1,147 | 12,952 |
| Education | 2,365 | 13,098 | 2,238 | 14,015 | 2,107 | 15,223 | 2,123 | 12,82 |
| Recreation | 269 | 3,084 | 266 | 2,755 | 266 | 4,219 | 253 | 3,15 |
| Clothing | 13,248 | 62,707 | 12,907 | 79,29 | 12,906 | 64,884 | 13,679 | 73,949 |
| Food | 4,222 | 25,932 | 3,964 | 22,982 | 3,976 | 33,29 | 4,196 | 24,215 |
| Cereal | 161 | 3,679 | 266 | 5,531 | 306 | 7,036 | 193 | 7,196 |
| Meat | 738 | 40,735 | 464 | 12,431 | 491 | 25,957 | 348 | 12,062 |
| Fish | 1,157 | 17,986 | 1,394 | 24,71 | 1,301 | 19,965 | 1,261 | 28,259 |
| Milk | 17,781 | 75,832 | 18,821 | 71,951 | 17,792 | 62,009 | 16,85 | 57,479 |
| Fruits and vegetables | 5,464 | 18,215 | 5,985 | 16,688 | 7,678 | 18,762 | 8,913 | 16,799 |
| Observations | 38,483 | | 38,400 | | 40,171 | | 41,544 | |

education, recreation, clothing and footwear, tobacco, alcohol), and total food expenses (i.e., cereal, meat, fish, milk, fruits and vegetables)[16]. In order to account for the different consumption needs of children and adults, we have recalculated the expenditure values to reflect the per-adult-equivalent using the OECD modified scale.[17] To control from the influence of commodity prices on the total value of expenditures, we have deflated the expenditures to their 2006 purchasing power equivalent using region- and good-specific CPIs.

Similarly, in analyzing income, we utilize both the total income values and the detailed income data, disaggregated by economic sector (i.e., net income from crop farming and gardening, net income from livestock and poultry raising, net income from fishing, net income from forestry and hunting, income from wholesale and retail trade, net income from manufacturing, net income from community, social, recreational and personal services, net income from transportation communication and storage, net income from mining and quarrying, net income from construction, and net income from entrepreneurial activities, and total cash receipts and assistance from abroad, total cash receipts and assistance from domestic).

Our analysis also considers the heterogeneity in impacts depending on a wide range of sociodemographic characteristics included in the FIES, such as food-poverty status[18], household size, urban or rural residence status, gender, age, marital status, employment status, and education of household head. Additionally, we consider income, building type, material for roof and wall, and an agricultural livelihood indicator[19].

## Climate Data

We focus our analysis on the impacts of two TC hazards, namely, wind and associated precipitation (or precipitation that occurs during a TC event). We anticipate that the nature of effects of the two hazards differ. On one hand, wind speeds of a certain magnitude can cause sudden, total destruction to physical properties, particularly when the building materials used and structures are not robust enough. Impacts from wind can, therefore, be correlated to household income, wherein richer households are able to afford sturdier houses that also protect all their assets within their houses from wind damage. On the other hand, flood-inducing precipitation causes wide-spread and location-specific damages, regardless of the household's financial capacity. Properties can be submerged in water for an extended amount of time and can impose prolonged disruptions and high repair costs on all assets within the house and on the house itself.

Acknowledging the presence of three hazards associated with TCs - wind, precipitation, and storm surge - we have opted to incorporate only two of these variables into our analyses. While we recognize the significant impact of storm surges in elevating the risk of flooding,

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[16] In order to minimize memory bias, the FIES uses an "average week" concept for all food expenditures. This differs from housing and utilities expenditure, where an "average month" concept is used. All other expenditures refer to the "past six months".

[17] The head of the household, other adults excluding the head of household (a) and children (c) are given weights $\alpha = 1$, $\delta = 0.5$, $\theta = 0.3$, respectively. FIES expenses are converted into per-adult-equivalent expenses using $(1 + \delta(a) + \theta(c))^{\alpha}$.

[18] The food-poor indicator is a binary variable where 1 signifies food-poor and 0 if not. A household is food-poor if the total household income falls below an income threshold required to meet basic food needs and to satisfy the nutritional requirements per capita based on standards set by the Food and Nutrition Research Institute (FNRI). The annual per capita food and poverty thresholds are found in the PSA's website: https://psa.gov.ph/poverty-press-releases/data. Accessed on August 11, 2022.

[19] The agriculture indicator is a binary variable where 1 signifies that the main source of income for the household is agriculture and 0 if not.

especially in coastal regions, we postpone a thorough analysis of storm surge impacts to future work. This is due to two reasons: First, robust data validation at the very local scale was not feasible. Second, we lack a robust damage function, analogous to the wind damage index utilized in our study, to integrate storm surge data according to our needs.

As an additional weather-related hazard that could influence the capacity of households to earn income and the need for additional expenditures, we also control for annual temperature changes[20]. Regional temperature variations can act as a proxy for TC frequency and intensity, e.g., modulated by the El Nino Southern Oscillation (ENSO) phenomenon[21].

## Wind

We obtain our wind speed data from the global data set of tropical cyclone exposure (TCE-DAT) (Geiger et al. 2018). TCE-DAT provides grid-level estimates of all land areas exposed to wind speeds exceeding 34 kn (63 kph), covering all TCs documented by the International Best Track Archive for Climate Stewardship (IBTrACS) (version v03r09). For each TC, a wind field model is applied that specifies the maximum wind speed of the storm at each location on a spatial scale of $0.1° \times 0.1°$. A total of 73 tropical cyclones were recorded to have made landfall in the Philippines between 2004 and 2015[22]. The frequency distribution of wind speeds in each municipality and storm from 2004-2015 is shown in Fig. 2.

For each of the 73 TC events, we calculated a scaled wind damage index for each municipality and storm ($W_{m,s}$) using the damage function in Emanuel (2011), Strobl (2019), and Skoufias et al. (2020), wherein the wind speed value ($k_{m,s}$) is normalised with respect to two thresholds in terms of property destruction. The first threshold corresponds to the minimum wind speed at which property damages start ($w_{threshold}$). The second threshold corresponds to the wind speed at which the value of the exposed property is halved ($w_{half}$). Based on the thresholds used by Emanuel (2011), Strobl (2019), and Skoufias et al. (2020), damages begin to occur at 50 kn ($\sim$ 93 kph) and half of the property is destroyed at 110 kn ($\sim$ 204 kph), see Eqs. 1 and 2, and a graphical representation of the index value relative to wind speed in Fig. 1. We will further discuss our adjustments to this index in the methodology section.

$$W_{m,s} = \frac{w_{m,s}^3}{1 + w_{m,s}^3} \tag{1}$$

$$w_{m,s} = \frac{max[k_{m,s} - w_{threshold}, 0]}{w_{half} - w_{threshold}} \tag{2}$$

We temporally aggregate the wind index values to an annual value per municipality by calculating the cumulative wind damage index by summing of all wind damage indices within a year, capped at 1 (i.e., representing total destruction of all property).

The cumulative wind damage index has three main advantages, as opposed to using raw wind speed data: first, we are able to account for the non-linear scaling of damages with wind speed (Geiger et al. 2016); second, we are able to account for multiple exposure to TCs within a year; and third, we are able to represent an upper limit to wind damages (i.e.,

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[20] We use 2m air temperature from ERA5-Land, which has a spatial resolution of 0.1° x 0.1°, and is available at an hourly frequency, to compute municipality-specific mean annual temperature (Munoz Sabater 2021).

[21] https://prsd.pagasa.dost.gov.ph/index.php/27-climatology-and-agrometeorology/1620-faq-for-el-nino. PAGASA FAQ for El Nino, accessed on March 25, 2024.

[22] Note that a TC in TCE-DAT is considered to make landfall once a portion of its wind footprint exceeding 34 kn touches land.
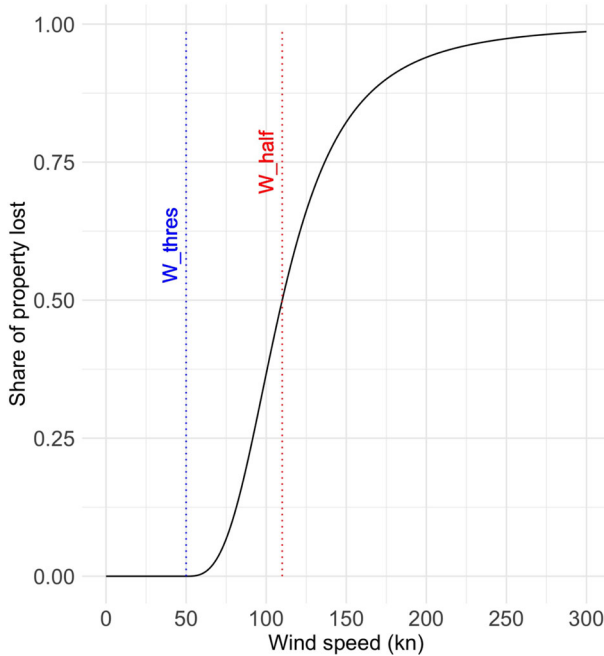
**Fig. 1** Graphical representation of the wind damage index, where damages start at 50 kn and half the property is destroyed at 110 kn

further exposure to higher magnitudes of wind will no longer cause additional damages to an already fully destroyed property).

## TC-Associated Precipitation

We obtain our precipitation data from the Global Precipitation Climatology Centre (GPCC, Full Data Daily Product V.2018 (V.2)), which contains records on global daily precipitation on the earth's land surface from more than 35,000 stations from 1982-2016 with a spatial resolution of $1.0° \times 1.0°$[23]. Because of its high temporal resolution, it is recommended to be used in analyses of extreme events (Schneider et al. 2018).

TC-associated precipitation may precede or extend after the occurrence of a TC's strongest winds. We base our definition of TC-associated precipitation by manually observing the days in which precipitation patterns coincide with IBTrACS storm dates. We spatially aggregate the TC-associated precipitation data to the municipality level by taking the average of daily precipitation of the grid cells that fall within the boundaries of each municipality. The frequency distribution of TC-associated precipitation in each municipality and storm from 2004-2015 is shown in Fig. 2.

For each of the 73 TCs we calculate the maximum 1-day precipitation (RX1d) for the relevant storm dates. In order to temporally aggregate the RX1d per TC event to an annual value, we aggregate the number of TCs in a year according to their specific RX1d intensity bin. The intensity bins are based on the quantile of wet days in months June-November of years

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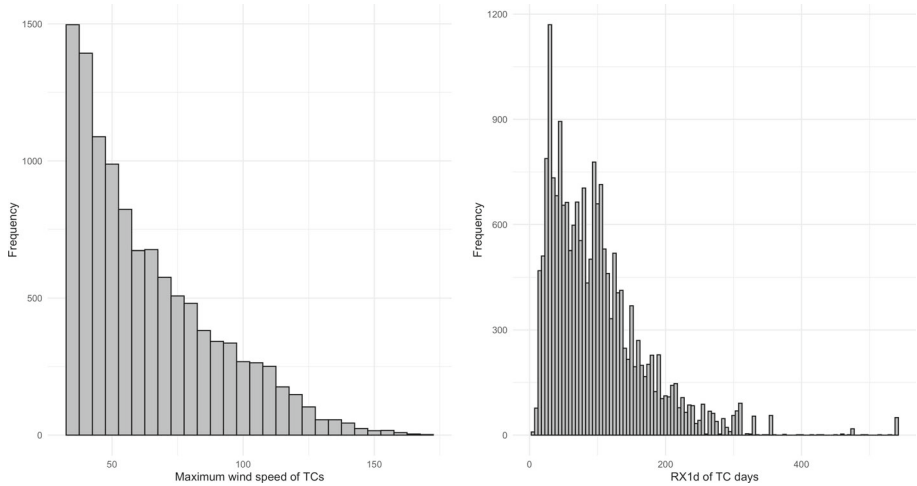
[23] Roughly 11 km x 11 km in the Philippines.

**Fig. 2** The frequency distribution of wind (left) and TC-associated precipitation (right) for each municipality from 2004-2015

2004-2015[24]. We expect municipalities to be affected by precipitation depending on their specific return level. For example, precipitation of 100mm within a 24-hour period may be an annual event for a specific municipality, wherein houses are elevated to a level that prevents flood waters from entering. The same amount could be a 1-in-100-year event for another municipality, in which households have no such precautions. Because of the heterogeneity of precipitation within the Philippines, we have opted for municipality-specific binning, rather than absolute bins; see Fig. 3 for the heterogeneity of precipitation quantiles across municipalities.

To define the extreme precipitation, we adopt a general approach of taking the 90th percentile of wet days as the relative threshold (Seneviratne et al. 2021). To account for multiple events of the extreme magnitudes, we represent our non-TC precipitation index (R90p index) on this definition by calculating the number of days that exceed the 90th percentile of wet days' daily precipitation (Karl et al. 1999).

## Methodology

The two main methodological contributions of this analysis are the locally informed adjustment of the vulnerability representation in the wind damage function, and the inclusion of two TC-associated hazards - wind and precipitation - in estimating the total TC impact on household wellbeing.

### Locally-Informed Scaled Wind Damage Index

The damage thresholds, in relation to wind speed given in Eq. 2, are based on a study in the US, and are likely underestimating the vulnerability of a developing country like the Philippines to TC wind speeds. In order to validate the current thresholds, we compare them

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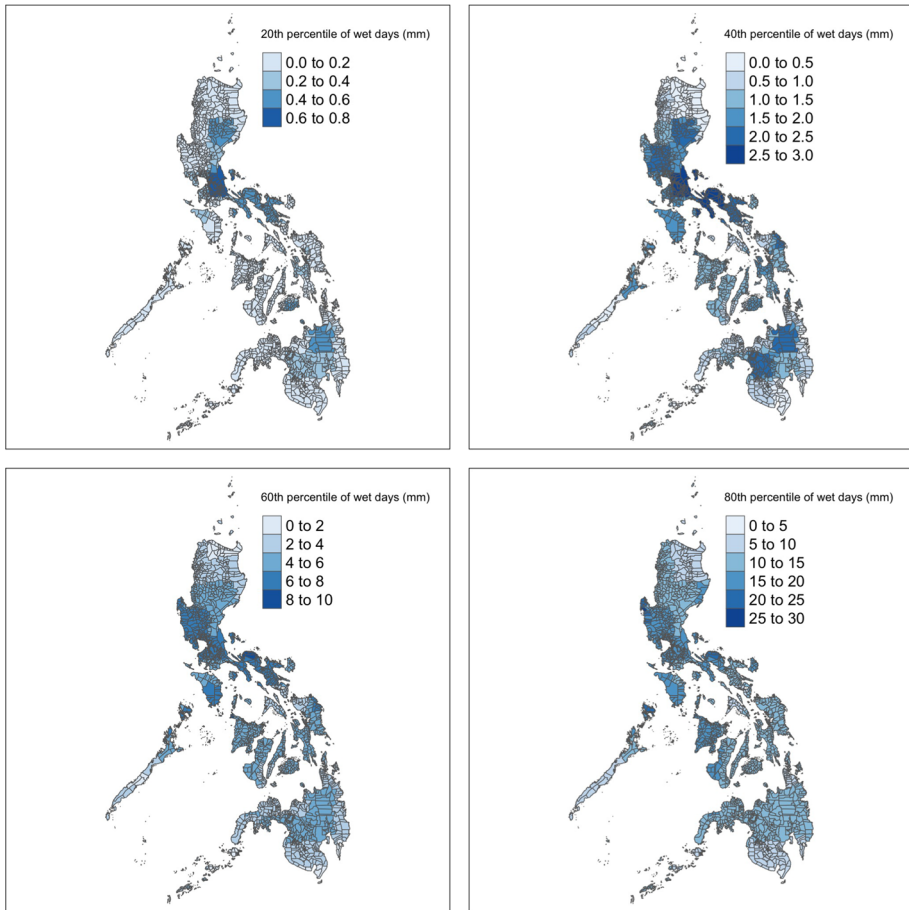[24] These months are indicated as the wet season by PAGASA.

**Fig. 3** Overview of municipality-specific quantiles (20th, 40th, 60th, 80th percentile) of daily precipitation based on wet days only

to local TC warnings to have an insight on the level of wind speed which damages start to occur, and the wind speed at which a significant amount of property is destroyed. Altering the minimum and the half-damage thresholds has implications on which areas are exposed to a TC, and the magnitude of destruction of exposed assets.

Anything below the minimum damage threshold would have a similar model representation as "no exposure" to TCs. By adjusting this threshold, we influence the number of areas exposed to TCs in the model, and consequently, also vulnerable to impacts. For instance, by lowering the threshold, we are able to acknowledge that wind speeds below 50 kn can affect households with houses built from very weak materials (i.e., in the case of informal settlers) or outdoor and resource-dependent livelihoods that are interrupted due to even a forecast of a TC.

The half-damage threshold already assumes exposure, and indicates the propensity of exposed assets to be destroyed. A high threshold implies that exposed assets are affected, but it would take stronger wind speeds to completely destroy the asset. This could be the case where areas are exposed and affected, but due to immediate post-disaster responses and

support, assets are salvaged, or immediately repaired. On the other hand, a low threshold implies that assets are easily destroyed once exposed. In reference to Fig. 5, all cumulative indexes greater than 1 are represented by 1 in the regression. The consequence of this is that the fastest wind speeds have the same value as weaker ones, which creates a noisy outcome for impacts on specific sectors[25].

Previous studies (e.g., Baldwin et al. 2023; Elliott et al. 2015) have adjusted only the half-damage threshold to account for different levels of vulnerability, without adjusting the minimum damage threshold. We argue in this study that adjusting both thresholds are important to account for local vulnerabilities, wherein a lower threshold in either one corresponds to higher vulnerability, and the distance between the two thresholds signify the speed of succession between assets being exposed to assets being destroyed.

In order to compare the damage function assumptions to actual experiences, we draw on the information from PAGASA as the local authority on weather-related events. For every TC, the PAGASA monitors the track of the storm, its wind speed and the amount of rainfall to be able to provide the necessary warning signals. These signals are identified by ordinal numbers 1-5, wherein a higher number signifies higher intensity of wind speeds. These signal numbers are closely and commonly associated by people in the Philippines to precautionary measures also issued by PAGASA, as well as their own experiences with a storm of similar intensity. We present the local PAGASA scale and the expected damages (PAGASA 2023) side-by-side with an international scale, such as the Saffir-Simpson scale in Fig. 4. We observe from the table that the lowest wind speed intensity of a local TC (signal number 1) starts at 34 kn ($\sim$ 63 kph), which is much weaker than a category 1 storm in the Saffir-Simpson scale (64 kn or $\sim$ 119 kph). Wind speed between 34-47 kn can already cause minor to moderate damages to buildings made of light or weakly constructed materials (e.g., houses of informal settlers and poor households whose roofs are made from makeshift galvanized steel), local power outages due to damages to electrical wires, minor to moderate disruption in transport. It can also cause considerable damage to agriculture, particularly rice and other similar crops at their flowering stages (PAGASA 2023).

In relation to the thresholds of the wind damage function, the minimum damage threshold of 50 kn corresponds to heavy damages to agriculture, particularly rice, banana, and similar crops[26], as well as substantial damages to infrastructure, particularly on poorly constructed houses, extended power outages, and some disruption in communications and potable water supply (PAGASA 2023). As a precautionary measure starting at 54kn, the Philippine government recommends taking shelter in strong buildings, evacuating low-lying areas, and staying away from coastal areas and riversides. Classes and offices in schools and universities are also cancelled in exposed areas (Government of the Philippines 2023).

At 110 kn where the model assumes that the value of properties are halved, PAGASA expects a majority of trees to be defoliated and uprooted, very few agricultural crops will survive, significant to catastrophic damages to well-built houses and industrial buildings, considerable airborne debris from roofs and glass windows being blown out, and the loss of power and water supply, as well as, transport interruptions for a prolonged period of time. With a TC of this intensity, the government warns the public of extremely catastrophic damages

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[25] We see evidence of this in our results, e.g., housing expenditures are significant for all threshold pairs, except the lowest threshold pair 34 kn-64 kn.

[26] The Philippines is the eight largest rice producing country (BusinessMirror 2022) and the second largest banana exporting country in the world (FAO 2023).

| Saffir-Simpson scale | Wind speed (kph) | Wind speed (kn) | PAGASA warning signals | PAGASA expected damages |
|---|---|---|---|---|
| Tropical depression | < 63 | < 34 | Signal no. 1 Tropical depression | Only very light or no damage |
| Tropical storm | 63 - 88 | 34 - 47 | Signal no. 2 Tropical storm | Light to moderate damages |
| Tropical storm | 89 - 118 | 48 - 63 | Signal no. 3 Severe tropical storm | Moderate to significant damages |
| Category 1 | 119 -151 | 64 - 81 | Signal no. 4 Typhoon | Significant to severe damages |
| Category 2 | 152 - 175 | 82 - 94 | Signal no. 4 Typhoon | Significant to severe damages |
| Category 3 | 176 - 207 | 95 - 111 | Signal no. 5 Super typhoon | Extreme threat |
| Category 4 | 208 - 251 | 112 - 135 | Signal no. 5 Super typhoon | Extreme threat |
| Category 5 | > 251 | > 136 | Signal no. 5 Super typhoon | Extreme threat |

**Fig. 4** Comparison of international and local wind scales. Note that the PAGASA warning signals have a slightly different range than the Saffir-Simpson scale, e.g., Signal no. 5 starts at 100kn

with a brief period of weakened winds in between strong winds of up to 2 hours when an area is directly at the eye of the storm (Government of the Philippines 2023). Evacuation operations should have already been completed, and emergency response groups are ready for deployment (Government of the Philippines 2023).

In light of these expected damages, we find it reasonable to test alternative damage thresholds in our regressions. We compare the results from four threshold pairs: (a) significantly lowering the minimum damage and the half-damage thresholds to 34 kn and 64 kn, respectively; (b) significantly lowering the minimum damage threshold to 34 kn, while keeping the slightly lowered half-damage threshold at 100 kn; (c) slightly lowering the minimum damage and the half-damage thresholds to 48 kn and 100 kn[27], respectively; and (d) keeping the thresholds of 50 kn and 110 kn for the minimum damage and the half-damage thresholds, respectively. The resulting cumulative wind scale calculations are shown in Fig. 5 [28]. The box plot shows that under the assumption of 50 kn-110 kn threshold pair, 7 out of 12 years would only have damages for municipalities whose wind speeds are considered outliers or values outside of the expected range of variation in the data[29]. Municipalities that have wind speeds within the expected range of variation will be assumed by the damage function to have no exposure to the TC event, which underestimates the actual number of municipalities exposed. In lowering the half-damage threshold to 64 kn, our results show lower, more homogenous impact estimates. This may be due to the upper bound limit of 1 for the damage index, which in the case of years 2004, 2006, 2009, 2013, 2014, and 2015 effectively reduces the values of the upper quantile to a lower magnitude.

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[27] 100kn is the start of signal no. 5 in the local scale.

[28] Values are capped at a maximum of 1 in the regressions, signifying total damage.

[29] The expected range of variation is computed by multiplying 1.5 to the interquartile range or the difference between the 75th and the 25th percentile.
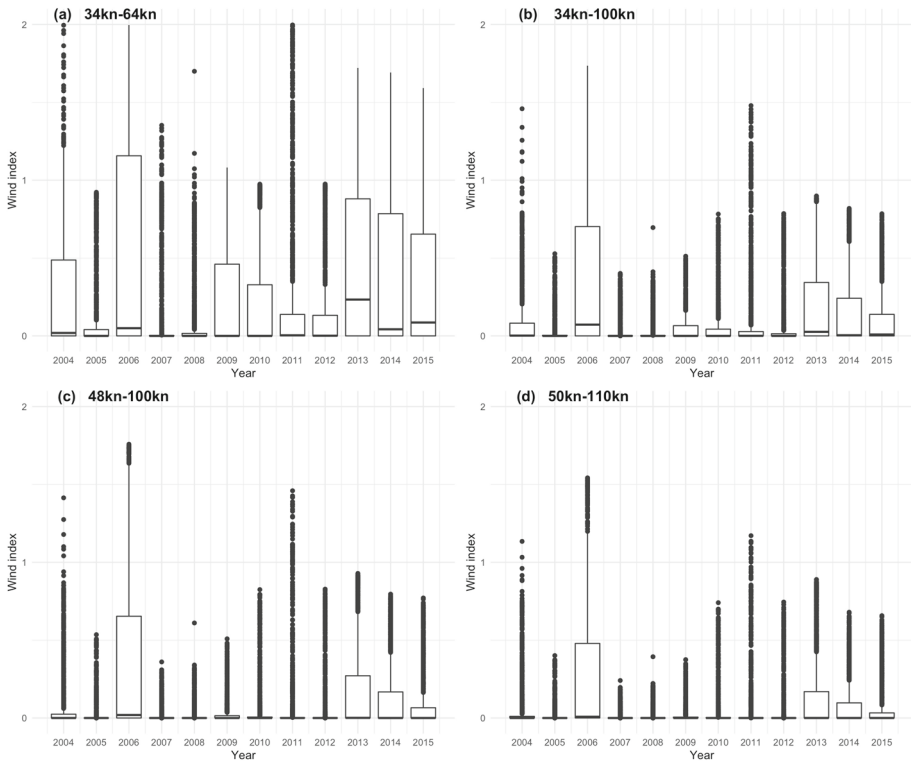
**Fig. 5** Scaled wind damage index with different minimum and half-damage thresholds. The box includes values between 25th and 75th percentile, the horizontal line in the box is the median, vertical lines outside of the box represent values that are within the expected range of variation, and the dots represent outliers

In order to capture impacts that are incurred by weaker wind speeds, while still considering extreme magnitudes of wind, we will consider 34 kn as the minimum damage threshold, and 100kn as the half-damage threshold (i.e., corresponding to the data shown in Fig. 5b) as our preferred wind damage specification for the main results of this paper. Further evidence for this choice will be presented in the results and discussion section of this paper.

### Regression Equation

To estimate the impacts of TC wind and associated precipitation on income and expenditure of households in the Philippines, we employ a fixed effects model as specified by equation 3:

$$ihs(y_{i,t}) = \alpha + \sum_{t=1}^{l} \beta_{w_{t-l}} w_{m,t-l} + \beta_{p_{t-l}} p_{m,t-l} + \beta_{c_{t-l}} c_{i,t-l} + \pi_t + \mu_i + \epsilon_{it}, \quad (3)$$

where $ihs(y_{i,t})$ is the inverse hyperbolic sine (ihs) of the pooled cross-section of expenditure and income categories of households ($i$) for FIES years ($t$) 2006, 2009, 2012, and 2015.

The transformation allows us to approximate a natural logarithm without sacrificing zero or negative values. [30]

We include the following independent variables: (1) the locally-adjusted cumulative wind damage index, ($W_{m,t-l}$), (2) the TC-binned precipitation, ($p_{t-l}$), and (3) weather-related [31] and household-related[32] control variables, ($c_{t-l}$). We include year ($\pi_t$) and region fixed effects ($\mu_i$), and the idiosyncratic error term ($\epsilon$). To account for possible spillover effects of TCs from previous (non-FIES) years, we include two years of lags ($l$) of TC wind and associated precipitation.

Based on the discussions in the previous section, the cumulative wind damage index will assume $w_{threshold}$ of 34 kn and $w_{half}$ of 100 kn, and sums all the indices for each storm in the year with a maximum value of 1. The formula for the cumulative wind damage index is given in Eq. 5, where $n$ is the number of TCs $s$ in year $t$ with lags $l$ from 0 to 2.

$$W_{m,t-l} = \sum_{1}^{n} \min \left( W_{m,s}, 1 \right) \tag{5}$$

We note that the resulting coefficients ($\beta$) of an arcsinh-linear model will closely approximate a log-linear model for large values, therefore, the same rules of interpretation of a log-linear model apply (Bellemare and Wichman 2020).[33]

We account for multiple hypothesis testing by applying the Benjamini-Hochberg procedure (Benjamini and Hochberg 1995), which controls for the expected proportion of falsely rejected null hypotheses (Type I error) among all rejected null hypotheses (i.e. the false discovery rate). By comparing the p-values from the regressions and the Benjamini-Hochberg adjusted p-values, we were able to verify the statistical significance of coefficients.

## Results and Discussion

### Impact Estimates from Different Wind Damage Thresholds

In line with the recent literature and in order to focus only in the variation in estimates due to the different wind damage thresholds discussed in the methodology section, we present in Fig. 6 the range of estimated impacts on income and expenditures from wind alone. The estimates were calculated by using the coefficients of the wind damage index multiplied by the wind damage index experienced by each municipality from 2004-2015, and provide the potential local impacts based on a country-wide average response. In addition, we provide a map showing the maximum estimated impacts in Fig. 7, in order to visualise the effects of the different thresholds in capturing the impacts from extreme TC wind speeds.

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[30] The formula for the ihs transformation is given by Eq. 4:

$$ihs(y) = arcsinh(y) = ln(y + sqrt(y^2 + 1)) \tag{4}$$

[31] I.e., mean annual temperature, and the R90p index for non-TC-associated precipitation days

[32] I.e., household size, urban or rural residence status, gender, age, marital status, employment status and education of household head, per capita income, building type, type of material for roof, type of material for wall, and agricultural livelihood indicator

[33] For large y, $\hat{\xi}_{yx} \approx \hat{\beta}x$, since $\lim_{y \to \infty} \frac{\sqrt{y^2+1}}{y} = 1$
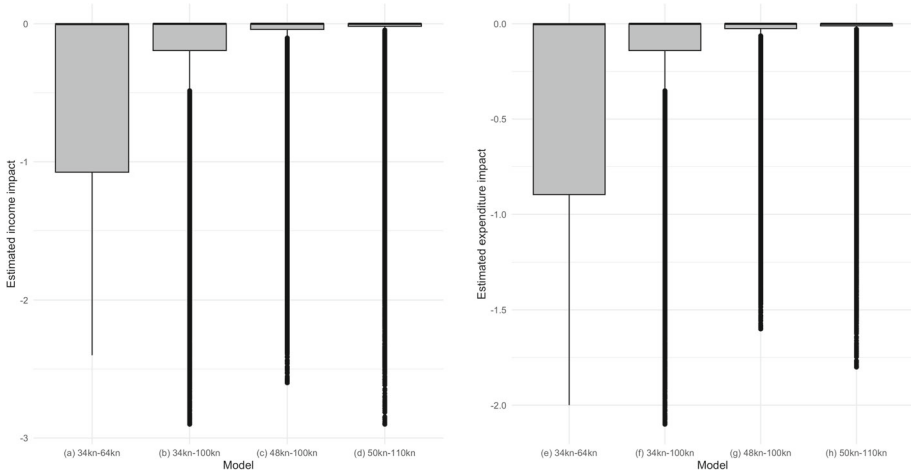
**Fig. 6** Estimated income (left) expenditure (right) impacts from wind using different damage thresholds

The results show that lowering the minimum damage threshold, $w_{threshold}$, widens the interquartile range (represented by the grey boxes) that suggest a higher variability in the observations (comparing the plots from right to left, as in Fig. 6 plots d to a, and h to e). The higher variability is coming from the increase in the number of areas considered by the damage function as affected by TC winds.

Meanwhile, lowering the half-damage threshold, $w_{half}$, results in a shorter range of extreme values (comparing the plots in Fig. 6 b to a, d to c, f to e, and h to g), which prohibits the representation of the most extreme TCs. We present evidence for this in Figs. 7a and 7e (left-most maps), where estimated impacts are not only lower than the results from the other damage thresholds, but also homogeneously distributed across affected areas.

Based on these findings, we substantiate our preference to use the damage thresholds of 34 kn and 100 kn as the minimum and half-damage threshold, respectively. Using these preferred damage thresholds, the estimated impacts within the country ranges from 0 to 2.9% reduction in total household income, and from 0 to 2.1% reduction in total household expenditure.

We now jointly evaluate the influence of wind and TC-associated precipitation to estimate the total TC impact. We calculated the impacts by multiplying the mean wind and associated precipitation value in each bin experienced by each municipality from 2004-2015 to the country-wide average response estimated by our regression.

Using Fig. 8 as reference, we observe two things. First, that the estimated average impacts on both income and expenditure from TC-associated precipitation (-6.7% and -6.2%, respectively) are substantially greater compared to the impacts from TC wind (-0.3% and -0.2%, respectively), thereby increasing the total estimated impact of TCs on expenditure and income. [34] Second, the affected areas of TC-associated precipitation differ from the ones exposed to wind. These results strongly suggest that estimates from wind speed alone do not only underestimate the magnitude of the TC impact, but also under-represent the number of affected areas.

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[34] The maximum total estimated impacts (i.e., both from wind and precipitation) within the country range is -24.4% for income and -23.6% for expenditures, of which -21.5 percentage points for both income and expenditures are contributed by TC precipitation.
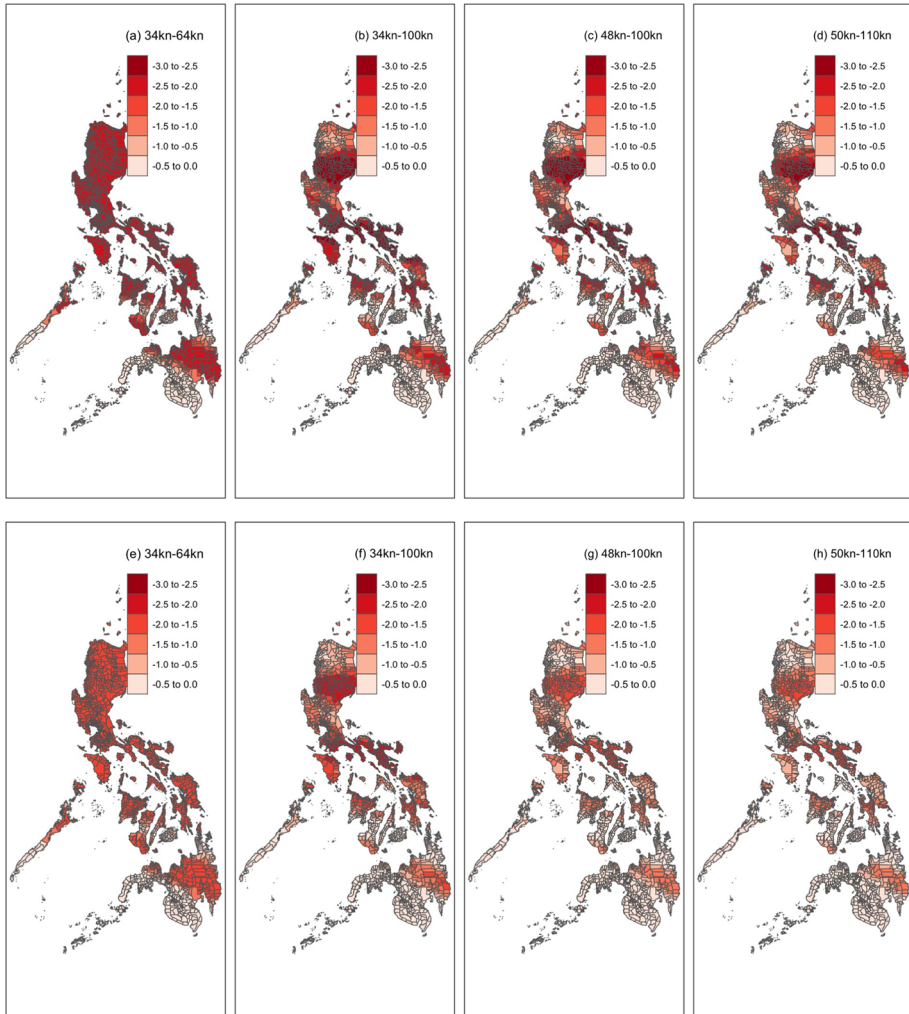
**Fig. 7** Estimated percent changes in total income (a-d) and total expenditure (e-h) using different wind damage thresholds, as presented in Fig. 5. The estimates are calculated using the coefficients of the wind damage index multiplied by the max wind damage index experienced by each municipality from 2004-2015

Comparing only the magnitudes of impact between income and expenditure, we also deduce that, at the aggregate level and using a country-wide response estimate, households are either unable to consumption-smooth or deliberately choosing to reduce consumption due to other preferences (e.g., asset preservation) in the event of an income shock. That is, a reduction in income almost completely corresponds to a reduction in the amount of goods and services purchased by the household.

## Subcategorical Analysis

In this section, we further investigate the source of these reductions, in order to reveal the potential impacts of TCs on different economic sectors. We aim to identify particularly
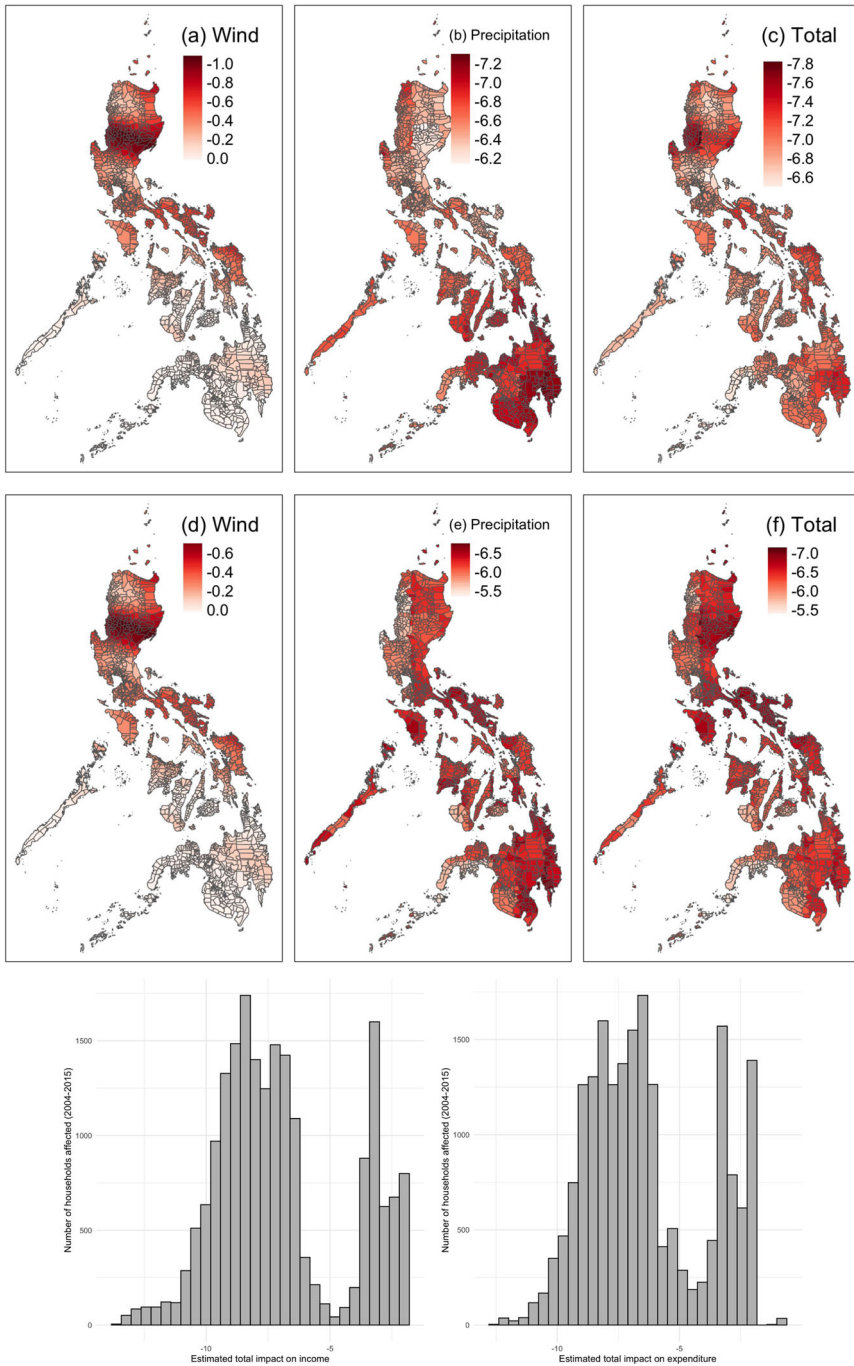
**Fig. 8** Comparison of impacts from wind and associated precipitation on income (a-c) and expenditure (d-f) in percent, and the number of municipalities with an expected level of impact on income (bottom left) and expenditure (bottom right). The impacts are calculated using the mean wind and precipitation bin experienced between 2004-2015 by municipality, and multiplying these with the estimated regression coefficients

vulnerable sectors, considering both supply reductions and substitution effects given the households' budget constraints. We are particularly interested in the ability (or disability) of households to smoothen consumption, as well as, their corresponding coping strategies. In addition, we relate the empirical estimates to lived realities and public and private disaster risk reduction measures discussed in the introduction.

### Income

Comparing the estimated reduction in total household income (same model estimates used in Figs. 8a, 8b, and 8c) and that from total income less transfers in Table 2), we find that cash transfers, through public cash transfer programs and other private financial sources (e.g., local support from relatives and communities, and remittances from abroad), may present an important tool in reducing income losses due to TCs.

The income sectors that are significantly affected by TCs are shown in Table 2. On average, livestock and poultry raising income is reduced by 15.4% and entrepreneurial activities by 4.2%.[35] These impacts are likely due to the destruction of barns, sties and coops for livestock; as well as the disruption in entrepreneurial activities due to dangerous conditions (e.g., flying debris and roofs outdoors). The impacts from TC-associated precipitation negatively affect a different set of sectors: fishing (-31.8%) and mining and quarrying (-3.1%)[36]. Fishing activities can be affected by heavy rain and flooding due to the overgrowing of algae blooms, known as "Red Tide" due to the discoloration of water along the coastline, which can be dangerous for marine life, and human life when fish and other seafood are consumed[37]. During Red Tide, the government[38] issues alerts, wherein people are warned not to consume any seafood, particularly shellfish, in affected areas, which is likely to affect both income and expenditures on seafood. The estimated reduction in mining income may be due to interrupted mining activities due to high risk of landslides and other casualties from heavy rainfall.[39]

On the other hand, our results show positive responses to TC-associated precipitation in wholesale and retail trade (60%), manufacturing (3%), and entrepreneurial activities (12.9%)[40].

While we expected adverse effects on crop farming due to either wind or associated precipitation, our results show no significant impacts. This result may be due to the strong support on immediate recovery, such as seed support programs that aim to replace damaged crops to catch up with harvest periods. The seed support program was particularly prominent during Typhoon Haiyan, where foreign donors have filled in for about 75% of the needed rice seed supply (FAO 2013). However, the same type of "catch-up" support is not available for the sectors where we see negative impacts.

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[35] The estimated reduction is calculated by multiplying the coefficient and the average wind damage index value of all municipalities from 2004-2015: 0.31.

[36] The estimated reduction is calculated by multiplying the coefficient and the average number of TC in precipitation bins in all municipalities from 2004-2015: 0.3 between 20th and 40th percentile, and 1.1 between 60th and 80th percentile of precipitation during wet days.

[37] Source: NOAA Scijinks. https://scijinks.gov/red-tide/. Accessed on March 24, 2024.

[38] In particular, The Bureau of Fisheries and Aquatic Resources (BFAR).

[39] The suspension in mining activities is implemented by law, based on the DENR Administrative order number 97-30 of 1997.

[40] The estimated reduction is calculated by multiplying the coefficient and the average number of TC in precipitation bins in all municipalities from 2004-2015: 0.3 between 20th and 40th percentile, and 0.5 between 40th and 60th percentile of precipitation during wet days, and 4.1 above 80th percentile.

**Table 2** Summary of regression results on income

| | Dependent variable | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Total income (1) | Income less cash transfers (2) | Livestock and poultry raising (3) | Fishing (4) | Wholesale and retail trade (5) | Manufacturing (6) | Mining and quarrying (7) | Income from entrepreneurial (8) |
| Wind | −0.029*** | −0.042*** | −0.492*** | −0.038 | −0.181 | 0.033 | 0.074 | −0.133*** |
| | (0.004) | (0.010) | (0.079) | (0.097) | (0.108) | (0.062) | (0.062) | (0.025) |
| Rain 20%<40% | −0.014*** | −0.037*** | 0.098 | −0.162* | 0.120** | 0.033 | −0.023 | 0.020 |
| | (0.003) | (0.005) | (0.056) | (0.076) | (0.040) | (0.023) | (0.013) | (0.015) |
| Rain 40%<60% | −0.013*** | −0.031*** | 0.018 | −0.087 | 0.098 | 0.056* | −0.015 | 0.011 |
| | (0.003) | (0.005) | (0.043) | (0.076) | (0.052) | (0.022) | (0.019) | (0.014) |
| Rain 60%<80% | −0.014*** | −0.026*** | 0.040 | −0.240** | 0.090 | 0.033 | −0.028* | 0.026* |
| | (0.003) | (0.005) | (0.046) | (0.076) | (0.047) | (0.025) | (0.014) | (0.013) |
| Rain >80% | −0.010*** | −0.024*** | 0.063 | −0.141 | 0.137** | 0.050* | −0.021 | 0.028* |
| | (0.002) | (0.004) | (0.048) | (0.080) | (0.047) | (0.025) | (0.016) | (0.014) |
| Observations | 634,120 | 634,120 | 634,120 | 634,120 | 634,120 | 634,120 | 634,120 | 634,120 |
| $R^2$ | 0.960 | 0.739 | 0.087 | 0.127 | 0.084 | 0.019 | 0.020 | 0.021 |
| Adjusted $R^2$ | 0.960 | 0.739 | 0.087 | 0.127 | 0.084 | 0.019 | 0.020 | 0.021 |

All models include 2 years of lags, household and non-TC weather control variables, and year and region fixed effects

*Note:* *$p<0.05$; **$p<0.01$; ***$p<0.001$

## Expenditures

We focus the discussion on non-food expenditures on three groups: housing-related expenditures, health expenditures, and expenditures on education. Table 3 presents the impacts on non-food expenditures.

We find that only housing expenditures (1.4%) are significantly affected by wind[41]. The increase in housing expenses include repairs that high wind speeds may have damaged.

The impacts of TC-associated precipitation, on the other hand, positively affect educational expenses. There are two possible explanations for the increase in educational expenses relating to the short-run and the long-run needs. In the short-run, the additional expenses may be due to the replacement of learning materials and the inflated transportation costs as mentioned also by Cadag et al. (2017). Despite the additional costs, some households choose to continue schooling for its long-run benefits. That is, Filipinos consider emigration as a coping mechanism to disaster-related impacts, where the correlation between educational attainment and the likelihood of migration is high (OECD/Scalabrini Migration Center 2017; International Organization for Migration (IOM) 2021). Filipinos with upper secondary and post-secondary education are more likely to emigrate than those with lower educational attainment (OECD/Scalabrini Migration Center 2017). It is also a common practice for emigrants to send remittances which make up about 10% of the country's GDP (OECD/Scalabrini Migration Center 2017). The remittances circle back to increasing educational expenditures for local family members to encourage emigration in the future (OECD/Scalabrini Migration Center 2017).

Despite our hypothesis that health expenditures will increase, we do not find significant effects of TCs on health expenditures. Our expectations are based on the increased threat on human health due to flooding and physical injuries from strong winds, as well as the insufficient coverage of health insurances. While 68.3% of the population has at least one form of health insurance (Philippine Statistics Authority 2017), out-of-pocket expenditures still make up half of the total health expenditures (World Health Organisation)[42]. The non-responsiveness of health expenditures to TC hazards can be attributed either the effective social programs attached to the disaster risk reduction strategy or to the common local behaviour of ignoring illnesses until they are unbearable, as mentioned in the introduction.

In terms of food expenditure, our results in Table 4 show that the reduction originates mainly from impacts on fish products (-53.1%), and fruits and vegetables (-45.2%)[43].

Similar to the effects on income, we attribute the reduction in fish consumption to episodes of "Red Tide". Due to impassable roads from high levels of flood water, the transport of fresh produce from far to market may be especially difficult.

We find no significant impact on cereals, despite potentially destructive effects on local food supply. Rice, in particular, is a staple food that is sensitive to disasters. The lack of response may be again attributed to government policies, where a significant amount of rice is included in food packs, as well as the effects of the intervention of the National Food Authority (NFA) under the DA on food prices. The NFA ensures price stability of rice by

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[41] The estimated impact is calculated by multiplying the coefficient and the average cumulative wind damage index value of all municipalities from 2004-2015: 0.31.

[42] Out of pocket expenditure (% of current health expenditure) as of 2017. Source: World Health Organization Global Health Expenditure database. The data was retrieved on January 30, 2022.

[43] The estimated reduction is calculated by multiplying the coefficients with the average value of precipitation bins.

**Table 3** Summary of regression results on non-food expenditures

| | Dependent variable | | | | |
| | Total expenditure (1) | Total non-food expenditure (2) | Housing (3) | Health (4) | Education (5) |
| --- | --- | --- | --- | --- | --- |
| Wind | −0.021** | −0.013 | 0.045* | −0.102 | 0.029 |
| | (0.007) | (0.010) | (0.018) | (0.053) | (0.062) |
| Rain 20%<40% | −0.009 | −0.002 | −0.027 | −0.016 | 0.190*** |
| | (0.005) | (0.007) | (0.015) | (0.036) | (0.044) |
| Rain 40%<60% | −0.011* | −0.003 | −0.012 | −0.028 | 0.141*** |
| | (0.005) | (0.008) | (0.011) | (0.028) | (0.038) |
| Rain 60%<80% | −0.014** | −0.004 | −0.010 | −0.047 | 0.145*** |
| | (0.005) | (0.008) | (0.014) | (0.029) | (0.044) |
| Rain >80% | −0.010* | −0.001 | −0.017 | 0.004 | 0.168*** |
| | (0.005) | (0.007) | (0.012) | (0.029) | (0.043) |
| Observations | 634,120 | 634,120 | 634,120 | 634,120 | 634,120 |
| $R^2$ | 0.887 | 0.868 | 0.798 | 0.238 | 0.273 |
| Adjusted $R^2$ | 0.887 | 0.868 | 0.798 | 0.238 | 0.273 |

All models include 2 years of lags, household and non-TC weather control variables, and year and region fixed effects

*Note:* *p<0.05; **p<0.01; ***p<0.001

**Table 4** Impact estimates on food expenditure categories

| | Dependent variable | | | | |
| | Total food expenditure (1) | Cereal (2) | Meat (3) | Fish (4) | Fruits and Vegetables (5) |
| --- | --- | --- | --- | --- | --- |
| Wind | −0.024* | −0.0002 | −0.028 | −0.051 | 0.014 |
| | (0.011) | (0.011) | (0.035) | (0.029) | (0.022) |
| Rain 20%<40% | −0.013 | 0.010 | 0.011 | −0.053* | −0.076*** |
| | (0.008) | (0.007) | (0.024) | (0.023) | (0.017) |
| Rain 40%<60% | −0.013 | 0.008 | 0.031 | −0.074*** | −0.067*** |
| | (0.008) | (0.006) | (0.021) | (0.022) | (0.017) |
| Rain 60%<80% | −0.020** | 0.001 | 0.053* | −0.105*** | −0.087*** |
| | (0.007) | (0.006) | (0.021) | (0.021) | (0.015) |
| Rain >80% | −0.017* | 0.005 | 0.023 | −0.087*** | −0.072*** |
| | (0.007) | (0.006) | (0.023) | (0.023) | (0.017) |
| Observations | 158,530 | 158,530 | 158,530 | 158,530 | 158,530 |
| $R^2$ | 0.712 | 0.115 | 0.413 | 0.137 | 0.312 |
| Adjusted $R^2$ | 0.712 | 0.114 | 0.412 | 0.137 | 0.311 |

All models include up to 2 years of lag, household and temperature control variables, and year and region fixed effects

*Note:* *p<0.05; **p<0.01; ***p<0.001

buying rice supply from local farmers and keeping them as buffer stocks for calamities and disasters.

## Adaptation due to Multiple TCs and the Vulnerability of the Poor

As discussed in the introduction, heterogeneity in impacts could also be linked to the likelihood and capacity to adapt. Households that have experienced extreme TCs (who are also likely to be exposed to TCs in the future) may have a higher inclination to adapt to the occurrence of TCs. On the other hand, certain groups, specifically poor households, have very limited capacity and resources to adapt, irrespective of their inclination to do so. In this section, we test for any difference in the estimated aggregate impacts if households are exposed to extreme TCs in a year or belong to the food-poor group. We apply an interaction

**Table 5** Summary of the effect of adaptation on total income and expenditures

|  | Dependent variable | |
|  | Total income (1) | Total expenditure (2) |
| --- | --- | --- |
| Wind | −0.037*** | −0.041** |
|  | (0.005) | (0.014) |
| Rain 20%<40% | −0.008** | 0.006 |
|  | (0.003) | (0.006) |
| Rain 40%<60% | −0.007* | 0.001 |
|  | (0.003) | (0.006) |
| Rain 60%<80% | −0.010*** | −0.0002 |
|  | (0.003) | (0.006) |
| Rain >80% | −0.004 | 0.004 |
|  | (0.003) | (0.006) |
| Number of TCs >95kn | −0.009 | 0.017 |
|  | (0.007) | (0.016) |
| Extreme rain | 0.002 | 0.036* |
|  | (0.007) | (0.015) |
| Wind:Number of TCs >95kn | 0.015 | −0.008 |
|  | (0.008) | (0.015) |
| Rain 20%<40%:Extreme rain | 0.001 | −0.008 |
|  | (0.002) | (0.005) |
| Rain 40%<60%:Extreme rain | 0.001 | 0.001 |
|  | (0.002) | (0.004) |
| Rain 60%<80%:Extreme rain | 0.004** | −0.006* |
|  | (0.001) | (0.003) |
| Rain >80%:Extreme rain | −0.001 | −0.006** |
|  | (0.001) | (0.002) |
| Observations | 634,120 | 634,120 |
| $R^2$ | 0.960 | 0.887 |
| Adjusted $R^2$ | 0.960 | 0.887 |

All models include 2 years of lags, household and non-TC weather control variables, and year and region fixed effects

*Note:* *p<0.05; **p<0.01; ***p<0.001

term to our wind and precipitation variables to identify any difference in estimated impacts compared to the total sample.

## Adaptation

We are interested in the interaction effect between our hazard variables and the exposure of the households to extreme wind and precipitation events, to understand if the latter provides any incentive to adapt - or conversely, a disincentive to invest in adaptation. We interact our wind variable to the number of times the household is exposed to TC with a minimum speed of 95 kn, and the precipitation variable with a binary variable indicating exposure to TC precipitation of at least the 90th percentile of wet days. When the coefficient of interaction partially or fully negates the coefficient of the primary variable, the result suggests stronger resilience on the part of households that experience TC events. If the two coefficients have the same sign, this suggests that impacts are aggravated by multiple occurrences.

Our results, shown in Table 5, suggest that there is no difference in wind-induced impacts on either income or expenditure. However, there is a partial offsetting of negative effect on income for households that have experienced extreme rainfall during a TC event. We still find a net negative effect on income and expenditures for both hazards.

## Poverty

In terms of poverty being a source of vulnerability, our results in Table 6 show that the impact of wind speed on the income of food-poor households does not differ from other households. Impacts from TC-precipitation show even a slightly higher resilience of household income to tropical cyclones (0.44 pp higher income than non-food-poor households)[44]. Government programs that combine disaster relief and response to poverty reduction programs in providing alternative income and cash transfers may have contributed to this effect.

On the other hand, in terms of expenditures, we find that the negative impacts from both wind and TC-associated precipitation are significantly higher for food-poor households (1.6 pp more expenditure impact on food-poor households)[45]. As we have seen in the aggregate income results in Table 2, households rely on in-kind and cash transfers to keep afloat after a disaster. However, challenges arise in the distribution of emergency aid, such as relief goods and services, when access to an area is restricted by environmental conditions. As noted by Tajo-Firmase et al. (2011), the distribution of relief goods and family hygiene kits have been delayed due to continuous heavy rain and flooding, especially affecting the poor where the nearest evacuation centers and distribution points were located in flooded areas.

## Conclusion

Our study contributes to improve TC impact assessments by drawing substantively on local knowledge to inform modelling assumptions on wind-related impacts, as well as the inclusion of flood-inducing precipitation as a compounding TC-associated hazard.

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[44] The impact is calculated using the resulting coefficient of the interaction term, multiplied by the average wind damage index value: 0.31.

[45] The impact is calculated using the resulting coefficient of the interaction term, multiplied by the average wind damage index value of 0.31, and TC precipitation between 60th and 80th percentile value of 1.12.

**Table 6** Summary of the effect of food poverty on total income and expenditures

| | *Dependent variable* | |
| | Total income (1) | Total expenditure (2) |
| --- | --- | --- |
| Wind | −0.026*** | −0.020* |
| | (0.004) | (0.008) |
| Food poor | −0.037*** | 0.055*** |
| | (0.004) | (0.008) |
| Rain 20%<40% | −0.010*** | −0.001 |
| | (0.002) | (0.006) |
| Rain 40%<60% | −0.008*** | −0.002 |
| | (0.002) | (0.006) |
| Rain 60%<80% | −0.010*** | −0.005 |
| | (0.002) | (0.006) |
| Rain >80% | −0.006** | −0.003 |
| | (0.002) | (0.005) |
| Wind:Food poor | −0.008 | −0.022** |
| | (0.005) | (0.009) |
| Rain 20%<40%:Food poor | 0.007*** | 0.0001 |
| | (0.001) | (0.002) |
| Rain 40%<60%:Food poor | −0.002** | −0.001 |
| | (0.001) | (0.003) |
| Rain 60%<80%:Food poor | 0.003** | −0.008** |
| | (0.001) | (0.003) |
| Rain >80%:Food poor | 0.001 | −0.001 |
| | (0.001) | (0.001) |
| Observations | 634,120 | 634,120 |
| $R^2$ | 0.960 | 0.887 |
| Adjusted $R^2$ | 0.960 | 0.887 |

All models include 2 years of lags, household and non-TC weather control variables, and year and region fixed effects

*Note:* *$p<0.05$; **$p<0.01$; ***$p<0.001$

The experience of the Philippines in being exposed to TCs multiple times in a year has motivated several advanced adaptation policies and strategies, both publicly and privately, specifically on emergency response and disaster risk reduction. Through our sub-categorical analysis of income and expenditure, we find that these efforts help in reducing impacts. In dampening the effects of TCs on income, for instance, we find that cash transfers – whether unconditional or in exchange of employment – are, not only reducing the negative effects on income, but they also serve to partially mitigate the unequal distribution of impacts through the implementation of combined disaster relief and poverty alleviation programs. On a private capacity, expenditures that ensure a more secure future - physically through shelter rebuilding and repair, as well as educational investments - are being employed by households. However, even with the extensive disaster risk reduction and management interventions, we still find adverse effects, particularly on food expenditures due to unavoidable consequences of strong winds and heavy rainfall on food supply.

We conclude that lowering the damage thresholds was an important step into capturing wind-related impacts in many vulnerable municipalities. We also strongly support the inclusion of TC-associated precipitation in the future assessments of TC impacts. For both income and expenditures, the omission of precipitation results in a significant underestimation of impacts, as well as, areas and economic sectors affected.

A limitation of our study is the analysed time period between 2004-2015, which does not capture the large improvements in the coordination of aid made after Typhoon Haiyan in 2013. Furthermore, our study looked at extremes experienced during a short period of time (i.e., maximum sustained wind speed and 1-day extreme precipitation) as proxies for the impacts, and does not include storm duration which might be more relevant for wind strain or the accumulation of rain over a longer periods of time. Similarly, storm surges are a relevant impact contribution at least for coastal communities that could so far not be included into the analysis due to data availability constraints.

Drawing from the results and our experience creating this paper, we recommend future research to focus on effective risk-reducing responses for the case of simultaneous occurrence of multiple TC hazards. In particular, challenges to reach and distribute food and non-food items (NFI) support in affected areas (e.g., flood-affected areas need a few days after the TC event until the water subsides as opposed to wind-stricken areas) and the concentration of areas where aid is delivered. Taken together, advances in scientific research on climate impacts and their implications on policy planning and implementation could contribute significantly to a targeted approach to reduce future climate risks.

## Appendix

We present in this annex alternative specifications to our regression model that we have considered, which support our decision in adopting our preferred specification presented in the methodology and results section of the main paper.

### Correlation Between Wind and Precipitation Magnitudes

In order to use TC-associated precipitation as a separate independent variable in our regression model, we show the absence of multicollinearity between TC wind and associated precipitation intensities using a Pearson correlation test. A scatter plot of the maximum wind and maximum 1-day precipitation of all 73 storms from 2004-2015 in each municipality shows only weak correlations, see Fig. 9.

### Transfers

The role of cash transfers in the reduction of TC impacts discussed in the section on climate data may be further broken down in two sources using the FIES data: cash from abroad, and cash from domestic sources. These refer to direct transfers to the households in the through public support programs or private remittances and support from local communities, family and friends. Table 7 shows that, while households in the Philippines have a stable stream of remittances from family abroad, we do not see a statistically significant effect on these transfers from abroad, depending on the magnitude of TC-associated hazards. However, we do find a strong increase in cash support from domestic sources depending on both wind and TC precipitation.
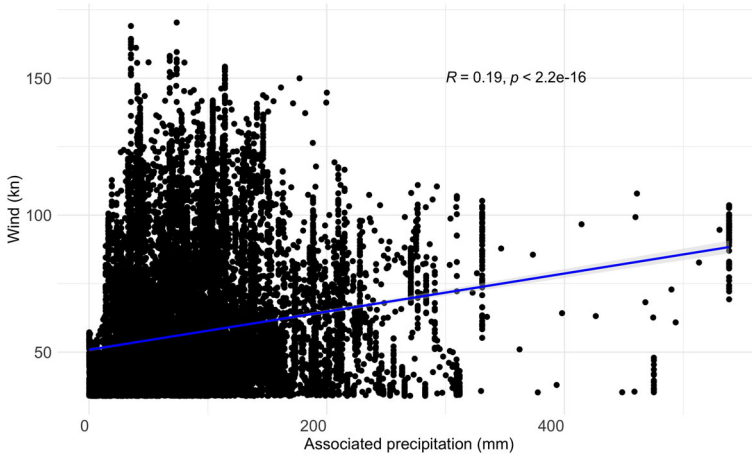
**Fig. 9** The correlation of the maximum sustained TC wind and maximum 1-day associated precipitation (RX1d) in each municipality of all TCs from 2004-2015

**Table 7** Transfers

| | Dependent variable | | | |
|---|---|---|---|---|
| | Total income (1) | Income less transfers (2) | Cash from abroad (3) | Cash from domestic (4) |
| Cumulative wind index | −0.029*** | −0.042*** | −0.181 | 0.604*** |
| | (0.004) | (0.010) | (0.098) | (0.126) |
| Rain [20%-40%) | −0.014*** | −0.037*** | 0.135 | 0.191 |
| | (0.003) | (0.005) | (0.081) | (0.099) |
| Rain [40%-60%) | −0.013*** | −0.031*** | 0.078 | 0.183* |
| | (0.003) | (0.005) | (0.080) | (0.086) |
| Rain [60%-80%) | −0.014*** | −0.026*** | 0.046 | 0.126 |
| | (0.003) | (0.005) | (0.090) | (0.095) |
| Rain >=80% | −0.010*** | −0.024*** | 0.075 | 0.237* |
| | (0.002) | (0.004) | (0.091) | (0.100) |
| Control variables | Yes | Yes | Yes | Yes |
| Lags | Yes | Yes | Yes | Yes |
| Fixed effects | Yes | Yes | Yes | Yes |
| Clustered SE | Yes | Yes | Yes | Yes |
| Observations | 634,120 | 634,120 | 634,120 | 634,120 |
| $R^2$ | 0.960 | 0.739 | 0.200 | 0.136 |
| Adjusted $R^2$ | 0.960 | 0.739 | 0.200 | 0.136 |

*Note:* *p<0.05; **p<0.01; ***p<0.001

## Normalised vs Non-Normalised Climate Variables

In this section, we compare the results of regressions using normalised indices introduced in the section on climate data and alternative non-normalised indicators. We, first, present the results on different wind specifications, keeping the precipitation specification the same (i.e., municipality-specific binned precipitation) as used in the methodology. Then, in the next subsection, we present the results on different precipitation specifications, keeping the wind specification the same (i.e., locally-adjusted cumulative wind damage index) as used in the methodology.

**Table 8** Estimated impacts on total income using different specifications of the wind variable

| | Dependent variable | | | |
| | Total Income | | | |
| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Max wind (kn) | −0.0003*** | | | |
| | (0.00002) | | | |
| Wind [34kn-63kn] | | −0.007*** | | |
| | | (0.001) | | |
| Wind [63kn-95kn] | | −0.009*** | | |
| | | (0.001) | | |
| Wind >= 95kn | | −0.016*** | | |
| | | (0.002) | | |
| Max wind damage index | | | −0.036*** | |
| | | | (0.005) | |
| Cumulative wind damage index | | | | −0.029*** |
| | | | | (0.004) |
| Rain 20%<40% | −0.015*** | −0.015*** | −0.013*** | −0.014*** |
| | (0.003) | (0.003) | (0.002) | (0.003) |
| Rain 40%<60% | −0.013*** | −0.014*** | −0.012*** | −0.013*** |
| | (0.003) | (0.003) | (0.002) | (0.003) |
| Rain 60%<80% | −0.014*** | −0.015*** | −0.013*** | −0.014*** |
| | (0.003) | (0.003) | (0.002) | (0.003) |
| Rain >80% | −0.008** | −0.009** | −0.008*** | −0.010*** |
| | (0.003) | (0.003) | (0.002) | (0.002) |
| Control variables | Yes | Yes | Yes | Yes |
| Lags | Yes | Yes | Yes | Yes |
| Fixed effects | Yes | Yes | Yes | Yes |
| Clustered SE | Yes | Yes | Yes | Yes |
| Observations | 634,120 | 634,120 | 634,120 | 634,120 |
| $R^2$ | 0.960 | 0.960 | 0.960 | 0.960 |
| Adjusted $R^2$ | 0.960 | 0.960 | 0.960 | 0.960 |

*Note:* *p<0.05; **p<0.01; ***p<0.001

**Table 9** Estimated impacts on total expenditure using different specifications of the wind variable

| | Dependent variable | | | |
| | Total Expenditure | | | |
| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Max wind (kn) | −0.0002*** | | | |
| | (0.00005) | | | |
| Wind [34kn-63kn] | | −0.009*** | | |
| | | (0.002) | | |
| Wind [63kn-95kn] | | −0.010** | | |
| | | (0.003) | | |
| Wind >= 95kn | | −0.016*** | | |
| | | (0.004) | | |
| Max wind damage index | | | −0.027*** | |
| | | | (0.008) | |
| Cumulative wind damage index | | | | −0.021** |
| | | | | (0.007) |
| Rain 20%<40% | −0.008 | −0.006 | −0.008 | −0.009 |
| | (0.005) | (0.005) | (0.005) | (0.005) |
| Rain 40%<60% | −0.008 | −0.008 | −0.009 | −0.011* |
| | (0.005) | (0.005) | (0.005) | (0.005) |
| Rain 60%<80% | −0.011* | −0.010* | −0.011* | −0.014** |
| | (0.005) | (0.005) | (0.006) | (0.005) |
| Rain >80% | −0.006 | −0.005 | −0.008 | −0.010* |
| | (0.005) | (0.005) | (0.005) | (0.005) |
| Control variables | Yes | Yes | Yes | Yes |
| Lags | Yes | Yes | Yes | Yes |
| Fixed Effects | Yes | Yes | Yes | Yes |
| Clustered SE | Yes | Yes | Yes | Yes |
| Observations | 634,120 | 634,120 | 634,120 | 634,120 |
| $R^2$ | 0.887 | 0.887 | 0.887 | 0.887 |
| Adjusted $R^2$ | 0.887 | 0.887 | 0.887 | 0.887 |

*Note:* *p<0.05; **p<0.01; ***p<0.001

## Comparison Using Different Wind Specifications

Tables 8 and 9 show the regression results using maximum wind in kn (column 1), binned wind in kn (column 2) and compare these with the results using the non-linear index for a single event (column 3), as well as the cumulative year index (column 4). Column 4 represents our preferred specification, therefore, it is identical with the results of total income and tota expenditures in Tables 2, 3, and 4. We use the same bounds for the non-normalised bins for maximum wind and the wind damage index for a better comparison of the two indicators.

As mentioned in the discussion in the section on climate data, there are several advantages to using the cumulative wind damage index. We find that the strongest argument to using the index is the limitation to damages once total destruction of property is reached. We can clearly visualise this in Fig. 10, where the results from binning the wind data are already much higher – than our estimates using the wind damage index (both max wind damage index and cumulative wind damage index), and could still increase even more if more that 2
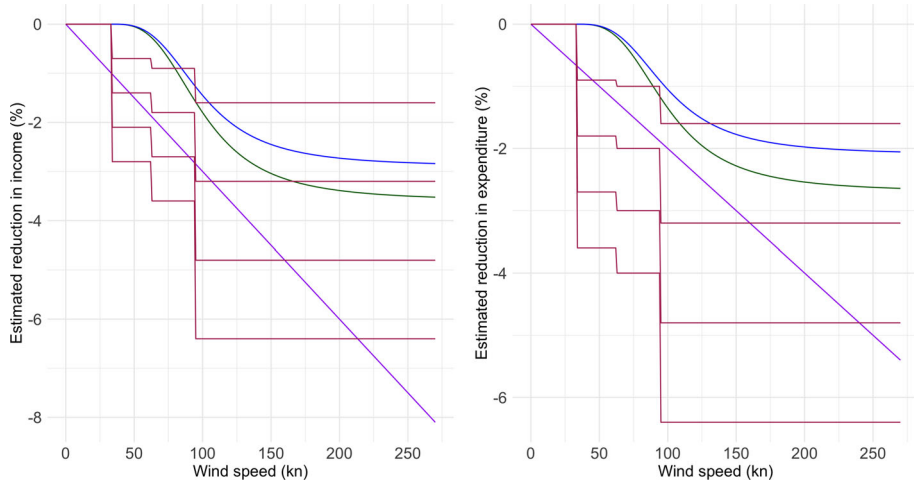
**Fig. 10** Estimated reduction in total income (left) and total expenditure (right) from wind alone using max wind in kn (purple), binned max wind with frequency of 1-4 times a year (maroon), max wind damage index (green), and cumulative wind damage index (blue)

TCs occur in a year. This supports the choice of using the wind damage index in the main text as being superior to using raw wind speeds (capturing only one TC in the year) or binned raw wind speeds (disregarding limits to property damage).

## Comparison Using Different Precipitation Specifications

In this section, we look at non-normalised TC-associated precipitation. Tables 10 and 11 show the regression results using maximum TC-associated precipitation (column 1), normalised TC-associated precipitation bins (column 2), and non-normalised TC-associated precipitation bins (column 3). For all three models, we include the cumulative wind damage index, which is the wind specification discussed in the results section of the main paper. In comparison to column 2, the range of each bin in column 3 is country-wide, rather than municipality-specific; and was computed by taking the country-wide quantiles of wet months from 2004-2015.

Except for a positive coefficient for the most extreme precipitation on income in column 3 of Table 10, we find all other coefficients not statistically significant. We expect that these results are due to the wide differences in "normal" precipitation experienced by different municipalities (see 3), such that absolute, country-wide binning thresholds result in mixed responses. That is, for municipalities that experience precipitation within their normal levels, there would be no significant impact. However, given the same amount of precipitation in a municipality that receives very little precipitation, it is likely to produce some disturbance to the households' economic activity. As mentioned also in the results section of our paper, Maquiling et al. (2021) provide information on how communities adapt to "normal" levels of flooding.

**Table 10** Estimated impacts on total income using different precipitation indicators

| | *Dependent variable* | | |
| | Total Income | | |
| | (1) | (2) | (3) |
|---|---|---|---|
| Cumulative wind damage index | −0.038*** | −0.029*** | −0.034*** |
| | (0.004) | (0.004) | (0.004) |
| Max rain | 0.0001*** | | |
| | (0.00001) | | |
| Rain [20%-40%) | | −0.013*** | |
| | | (0.002) | |
| Rain [40%-60%) | | −0.011*** | |
| | | (0.002) | |
| Rain [60%-80%) | | −0.013*** | |
| | | (0.002) | |
| Rain >=80% | | −0.008*** | |
| | | (0.002) | |
| Rain [0.19-1.4 mm/day) | | | 0.002 |
| | | | (0.002) |
| Rain [1.4-4.6 mm/day) | | | 0.002 |
| | | | (0.001) |
| Rain [4.6-13.3 mm/day) | | | 0.001 |
| | | | (0.002) |
| Rain >= 13.3 mm/day | | | 0.005*** |
| | | | (0.001) |
| Control variables | Yes | Yes | Yes |
| Lags | Yes | Yes | Yes |
| Fixed effects | Yes | Yes | Yes |
| Clustered SE | Yes | Yes | Yes |
| Observations | 634,120 | 634,120 | 634,120 |
| $R^2$ | 0.960 | 0.960 | 0.960 |
| Adjusted $R^2$ | 0.960 | 0.960 | 0.960 |

*Note:* *p<0.05; **p<0.01; ***p<0.001

**Table 11** Estimated impacts on total expenditure using different precipitation indicators

| | Dependent variable | | |
| | Total expenditure | | |
| | (1) | (2) | (3) |
|---|---|---|---|
| Cumulative wind damage index | −0.037*** | −0.021** | −0.023*** |
| | (0.006) | (0.007) | (0.006) |
| Max rain | 0.0001*** | | |
| | (0.00002) | | |
| Rain [20%-40%) | | −0.009 | |
| | | (0.005) | |
| Rain [40%-60%) | | −0.011* | |
| | | (0.005) | |
| Rain [60%-80%) | | −0.014** | |
| | | (0.005) | |
| Rain >=80% | | −0.010* | |
| | | (0.005) | |
| Rain [0.19-1.4 mm/day) | | | 0.003 |
| | | | (0.004) |
| Rain [1.4-4.6 mm/day) | | | 0.004 |
| | | | (0.005) |
| Rain [4.6-13.3 mm/day) | | | 0.002 |
| | | | (0.005) |
| Rain >= 13.3 mm/day | | | 0.004 |
| | | | (0.004) |
| Control variables | Yes | Yes | Yes |
| Lags | Yes | Yes | Yes |
| Fixed effects | Yes | Yes | Yes |
| Clustered SE | Yes | Yes | Yes |
| Observations | 634,120 | 634,120 | 634,120 |
| $R^2$ | 0.886 | 0.887 | 0.887 |
| Adjusted $R^2$ | 0.886 | 0.887 | 0.887 |

*Note:* *p<0.05; **p<0.01; ***p<0.001

## Declarations

**Competing interests** The authors declare no competing interests.

## References

Anttila-Hughes J, Hsiang S (2013) Destruction, disinvestment, and death: economic and human losses following environmental disaster. SSRN Electron J. https://doi.org/10.2139/ssrn.2220501

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

Baez JE, Lucchetti L, Genoni ME, Salazar M (2017) Gone with the storm: rainfall shocks and household wellbeing in Guatemala. J Dev Stud 53(8):1253–1271

Baez JE, Santos IV (2007) Children's vulnerability to weather shocks: a natural disaster as a natural experiment. Social Science Research Network, New York

Bakkensen LA, Park D-SR, Sarkar RSR (2018) Climate costs of tropical cyclone losses also depend on rain. Env Res Lett 13(7):074034. Retrieved 2022-11-04, from https://iopscience.iop.org/article/10.1088/1748-9326/aad056, https://doi.org/10.1088/1748-9326/aad056

Baldwin JW, Lee C-Y, Walsh BJ, Camargo SJ, Sobel AH (2023) Vulnerability in a tropical cyclone risk model: Philippines case study. Weather Clim Soc 15(3):503–523. Retrieved from https://journals.ametsoc.org/view/journals/wcas/15/3/WCAS-D-22-0049.1.xml, https://doi.org/10.1175/WCAS-D-22-0049.1

Bellemare M, Wichman C (2020) Elasticities and the inverse hyperbolic sine transformation. Oxford Bull Econ Stat 82(1):50–61. https://doi.org/10.1111/obes.12325

Benjamini Y, Hochberg Y (1995) Controlling the false discovery rate: a practical and powerful approach to multiple hypothesis testing. J Royal Stat Soc Ser B (Methodol) 57:289–300

BusinessMirror (2022) NSIC OKs 14 Rice Varieties Developed by IRRI, PhilRice. Retrieved from https://businessmirror.com.ph/2022/06/01/nsic-okays-14-rice-varieties-developed-by-irri-philrice/. Accessed 4 Sept 2023

Cadag JRD, Petal M, Luna E, Gaillard J, Pambid L, Santos GV (2017) Hidden disasters: recurrent ooding impacts on educational continuity in the Philippines. Int J Dis Risk Reduc S2212420917302200. https://doi.org/10.1016/j.ijdrr.2017.07.016

Chhibber A, Laajaj R (2008) Disasters, climate change and economic development in Sub-Saharan Africa: lessons and directions. J Afr Econ 17. https://doi.org/10.1093/jae/ejn020

Cinco T, Guzman R, Ortiz AM, Delfino RJ, Lasco R, Hilario F, Ares E (2016) Observed trends and impacts of tropical cyclones in the Philippines. Int J Climatol. https://doi.org/10.1002/joc.4659

Collalti D, Strobl E (2022) Economic damages due to extreme precipitation during tropical storms: evidence from Jamaica. Nat Hazards 110(3):2059–2086

Congress of the Philippines (2010) Republic Act No. 10121. Retrieved from https://www.officialgazette.gov.ph/2010/05/27/republic-act-no-10121/. Accessed 21 Sept 2023

Deuchert E, Felfe C (2015) The tempest: short-and long-term consequences of a natural disaster for children's development. Eur Econ Rev 80:280–294

Eberenz S, Lüthi S, Bresch DN (2021) Regional tropical cyclone impact functions for globally consistent risk assessments. Nat Hazards Earth Syst Sci 21:393–415. https://doi.org/10.5194/nhess-21-393-2021

Eckstein, D., Künzel, V., Schäfer, L. (2021). Global climate risk index 2021 (Tech. Rep.). German Watch, Germany

Elliott RJ, Strobl E, Sun P (2015) The local impact of typhoons on economic activity in China: a view from outer space. J Urban Econ 88:50–66. Retrieved from https://doi.org/10.1016/j.jue.2015.05.001

Emanuel K (2011) Global warming effects on U.S. hurricane damage. Weather Clim Soc 3(4):261–268. Retrieved from https://journals.ametsoc.org/view/journals/wcas/3/4/wcas-d-11-00007_1.xml, https://doi.org/10.1175/WCAS-D-11-00007.1

Espada, R. (2018). Return period and Pareto analyses of 45 years of tropical cyclone data (1970–2014) in the Philippines. Appl Geogr 97:228–247. Retrieved from https://www.sciencedirect.com/science/article/pii/S0143622817308391, https://doi.org/10.1016/j.apgeog.2018.04.018

FAO (2013). Planting the seeds of recovery in the Philippines after typhoon Haiyan. Retrieved from https://www.fao.org/in-action/plantingthe-seeds-of-recovery-in-the-philippines-after-typhoon-haiyan/en/. Accessed 20 Sept 2023

FAO (2023). Banana market review 2022. Rome. Retrieved from https://www.fao.org/markets-and-trade/commodities/bananas/en/

Geiger T, Frieler K, Bresch DN (2018) A global historical data set of tropical cyclone exposure (TCE-DAT). Earth Sys Sci Data 10(1):185–194. Retrieved from https://essd.copernicus.org/articles/10/185/2018/, https://doi.org/10.5194/essd-10-185-2018

Geiger T, Frieler K, Levermann A (2016) High-income does not protect against hurricane losses. Env Res Lett 11(8):084012. Retrieved from https://dx.doi.org/10.1088/1748-9326/11/8/084012

Geiger T, Gütschow J, Bresch DN, Emanuel K, Frieler K (2021) Double benefit of limiting global warming for tropical cyclone exposure. Nat Clim Chang 11(10):861–866. https://doi.org/10.1038/s41558-021-01157-9

GFDRR (2009). Philippines - 2009 - typhoons Ondoy and Pepeng affected 9.3 million people. Retrieved from https://www.gfdrr.org/en/philippines-2009-typhoons-ondoy-and-pepeng-affected-93-million-people. Accessed 22 Sept 2023

Government of the Philippines (2023). Official gazette website: Philippine public storm warning signals. Retrieved from https://www.officialgazette.gov.ph/laginghanda/the-philippine-public-storm-warning-signals/. Accessed 19 Oct 2023

Hallegatte S, Bangalore M, Bonzanigo L, Fay M, Kane T, Narloch U, Vogt-Schilb A, et al. (2015) Shock waves: managing the impacts of climate change on poverty. The World Bank, Washington, DC. Retrieved from https://openknowledge.worldbank.org/handle/10986/22787

Hallegatte S, Vogt-Schilb A, Rozenberg J, Bangalore M, Beaudet C (2020) From poverty to disaster and back: a review of the literature. Econ Dis Clim Change 4(1):223–247. Retrieved from https://doi.org/10.1007/s41885-020-00060-5

Henry M, Spencer N, Strobl E (2020) The impact of tropical storms on households: evidence from panel data on consumption. Oxford Bull Econ Stat 82(1):1–22. https://doi.org/10.1111/obes.12328

International Organization for Migration (IOM) (2021) Framing the human narrative of migration in the context of climate change: a preliminary review of existing evidence in the Philippines (Tech. Rep.) https://philippines.iom.int/sites/g/files/tmzbdl1651/files/documents/framing-the-human-narrative-of-migration-in-the-context-of-climate-change_0.pdf. IOM Philippines, Philippines

Ishizawa OA, Miranda JJ (2019) Weathering storms: understanding the impact of natural disasters in Central America. Environ Resource Econ 73(1):181–211

Karl TR, Nicholls N, Ghazi A (1999) CLIVAR/GCOS/WMO workshop on indices and indicators for climate extremes workshop summary. In: Karl TR, Nicholls N, Ghazi A (eds) Weather and climate extremes. Springer, Dordrecht. https://doi.org/10.1007/978-94-015-9265-9_2

Knutson T, Camargo SJ, Chan JCL, Emanuel K, Ho C-H, Kossin J et al (2020) Tropical cyclones and climate change assessment: Part ii. projected response to anthropogenic warming. Bull Am Meteor Soc 56:E303–E322. https://doi.org/10.1175/BAMS-D-18-0194.1

Krichene H, Geiger T, Frieler K, Willner S, Sauer I, Otto C (2021) Long-term impacts of tropical cyclones and pluvial floods on economic growth empirical evidence on transmission channels at different levels of development. World Dev 144:105475. Retrieved from https://www.sciencedirect.com/science/article/pii/S0305750X21000875, https://doi.org/10.1016/j.worlddev.2021.105475

Kunze S (2021) Unraveling the effects of tropical cyclones on economic sectors worldwide: direct and indirect impacts. Env Res Econ 78:545–569. https://doi.org/10.1007/s10640-021-00541-5g

Kure S, Jibiki Y, Iuchi K, Udo K (2016) Overview of super typhoon Haiyan and characteristics of human damage due to its storm surge in the coastal region, Philippines. In: Vila-Concejo A, Bruce E, Kennedy DM, McCarroll RJ (Eds) Proceedings of the 14th international coastal symposium. Coconut Creek (Florida), Sydney, Australia, pp 1152–1156

Lasco G, Yu V, David C (2022) The lived realities of health financing: a qualitative exploration of catastrophic health expenditure in the Philippines. Acta Med Philipp 56(11). https://actamedicaphilippina.upm.edu.ph/index.php/acta/article/view/2389

Lee T-C, Knutson TR, Kamahori H, Ying M (2012) Impacts of climate change on tropical cyclones in the western north pacific basin. Part i: Past observations. Trop Cyclone Res Rev 1(2):213–235. Retrieved from https://www.sciencedirect.com/science/article/pii/S222560321830033X, https://doi.org/10.6057/2012TCRR02.08

Lenzen M, Malik A, Kenway S, Daniels P, Lam KL, Geschke A (2019) Economic damage and spillovers from a tropical cyclone. Nat Hazard Earth Sys Sci 19(1):137–151. Retrieved from https://nhess.copernicus.org/articles/19/137/2019/, https://doi.org/10.5194/nhess-19-137-2019

Maquiling KSM, De La Sala S, Rabé P (2021) Urban resilience in the aftermath of tropical storm washi in the Philippines: the role of autonomous household responses. Env Plan B Urban Anal City Sci 48(5):1025–1041. https://doi.org/10.1177/2399808321998693

Muñoz Sabater J (2021) Era5land hourly data from 2006 to 2015. https://doi.org/10.24381/cds.e2161bac

OECD/Scalabrini Migration Center (2017) Interrelations between public policies, migration and development in the Philippines. OECD, Paris Publishing, Retrieved from. https://doi.org/10.1787/9789264272286-en

Office of the Civil Defense (2011) National disaster risk reduction and management plan 2011-2028. Accessed 21 Sept 2023

PAGASA (2023). Website: climate information. http://bagong.pagasa.dost.gov.ph/information/climate-philippines. Accessed 20 Nov 2020

PAGASA (2023). Website: tropical cyclone wind signal. https://www.pagasa.dost.gov.ph/learning-tools/tropical-cyclone-wind-signal. Accessed 19 Oct 2023

Philippine Statistics Authority (2015) Family income and expenditure survey 2015 (Tech. Rep.). Philippine Statistics Authority, Philippines. Retrieved from https://psa.gov.ph/statistics/income-expenditure/es. Accessed 22 Sept 2022

Philippine Statistics Authority (2017) Philippine national demographic and health survey 2017 (Tech. Rep.). Philippine Statistics Authority, Philippines

Pérez-Escamilla R, Moran VH (2023) Maternal and child nutrition must be at the heart of the climate change agendas. Matern Child Nutr 19(1):e13444. https://onlinelibrary.wiley.com/doi/abs/10.1111/mcn.13444https://arxiv.org/abs/https://onlinelibrary.wiley.com/doi/pdf/10.1111/mcn.13444https://doi.org/10.1111/mcn.13444

Rey A (2015) Timeline: Ph policies on climate change and disaster management. Accessed 21 Sept 2023

Sakai Y, Estudillo JP, Fuwa N, Higuchi Y, Sawada Y (2017) Do natural disasters affect the poor disproportionately? Price change and welfare impact in the aftermath of typhoon Milenyo in the rural Philippines. World Dev 94:16–26

Sato T, Nakasu T (2011) 2009 typhoon Ondoy ood disasters in Metro Manila. Natural disaster research report of the National Research Institute for Earth Science and Disaster Prevention p 45. https://dil-opac.bosai.go.jp/publication/nied_natural_disaster/pdf/45/45-04E.pdf

Schneider U, Becker A, Finger P, Meyer-Christoffer A, Ziese M (2018) GPCC Full Data Daily Version.2018 at 1.0°: daily Land-Surface Precipitation from Rain-Gauges built on GTS-based and Historic Data. Retrieved from https://opendata.dwd.de/climate_environment/GPCC/html/fulldata-daily_v2018_doi_download.html, https://doi.org/10.5676/DWD_GPCC/FD_D_V2018_100

Seneviratne S, Zhang X, Adnan M, Badi W, Dereczynski C, Luca AD, Zhou B et al. (2021) Weather and climate extreme events in a changing climate. In: Masson-Delmotte V, Zhai P, Pirani A, Connors SL, Péan C, Berger S, Caud N, Chen Y, Goldfarb l, Gomis MI, Huang M, Leitzell K, Lonnoy E, Matthews JBR, Maycock TK, Waterfield T, Yelekçi O, Yu R, and Zhou B (eds.) Climate change 2021: the physical science basis. contribution of working group 1 to the sixth assessment report of the intergovernmental

panel on climate change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA. https://doi.org/10.1017/9781009157896.013

Skoufias E, Kawasoe Y, Strobl E, Acosta P (2020) Identifying the vulnerable to poverty from Natural Disasters: the case of typhoons in the Philippines. Econ Dis Clim Change 4. https://doi.org/10.1007/s41885-020-00059-y

Strobl E (2019) The impact of typhoons on economic activity in the Philippines: evidence from Nightlight Intensity (ADB Economics Working Paper Series No. 589). Asian Development Bank. Retrieved from https://ideas.repec.org/p/ris/adbewp/0589.html

Tajo-Firmase J, Eugenio V, Bullo M, Shao Yi L, Gabriel D, Luna E (2011) Lessons and challenges in disaster relief operations for families affected by typhoon ondoy in rizal province. Philipp J Soc Dev 3. Retrieved from https://cswcd.upd.edu.ph/wp-content/uploads/2021/10/PJSD-Vol-3-2011_Firmase.pdf

UN OCHA (2009a) Philippines tropical storm Ketsana (Ondoy). Situation report no. 3. Retrieved from https://reliefweb.int/report/philippines/philippines-tropical-storm-ketsana-ondoy-situation-report-no-3. Accessed 22 Sept 2023

UN OCHA (2009b) Situation report Philippines- typhoon Ondoy. Retrieved from https://reliefweb.int/report/philippines/situationreport-philippines-typhoon-ondoy. Accessed 22 Sept 2023

UN OCHA (2017) Philippines: destructive tropical cyclones from 2006 to 2016. Retrieved from https://reliefweb.int/map/philippines/philippines-destructive-tropical-cyclones-2006-2016

UNDRR (2022) Web article: poverty and inequality. https://www.preventionweb.net/understanding-disaster-risk/risk-drivers/poverty-inequality. Accessed 21 June 2023

Villarin J, Algo J, Cinco T, Cruz F, de Guzman R, Hilario F, Tibig LV et al. (2016) Philippine climate change assessment (philcca): the physical science basis. The Oscar M. Lopez Center for Climate Change Adaptation and Disaster Risk Management Foundation, Inc. and climate change commission (Tech. Rep.). Philippines: Oscar M. Lopez Center for Climate Change Adaptation and Disaster Risk Management Foundation, Inc

Wahl T, Jain S, Bender J, Meyers S, Luther M (2015) Increasing risk of compound flooding from storm surge and rainfall for major US cities. Nature Clim Change 5:1093–1097. https://doi.org/10.1038/nclimate2736

Walsh B, Hallegatte S (2020) Measuring natural risks in the Philippines: socioeconomic resilience and well-being losses. Econ Dis Clim Change 4(2):249–293. Retrieved from https://ideas.repec.org/a/spr/ediscc/v4y2020i2d10.1007_s41885-019-00047-x.htmlhttps://doi.org/10.1007/s41885-019-00047

Yonson R, Noy I, Gaillard J (2018) The measurement of disaster risk: an example from tropical cyclones in the Philippines. Rev Dev Econ 22(2):736–765