CHIPS
Climate Change Impacts and Policies in Heterogeneous Societies

# Quantifying heterogeneous impacts of climate change for different income groups

Deliverable 2.1

JPI Climate AXIS

April 2023

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## Introduction

A literature review currently still under way indicates that knowledge on heterogeneous impacts of climate change is very scattered and largely qualitative (Méjean et al., in preparation). Quantitative studies are often not global or do not use economic indicators to quantify the results. This constitutes a problem for deriving policy advice in two areas. First, for designing useful and robust adaptation measures and policies underlying inequalities and related heterogeneous impacts must be known. Second, for integrated assessment modeling with a fairly high level of aggregation, there is currently no basis to quantify how aggregated climate change impacts on output should be distributed over different income groups, hampering the integrated analysis of transformation pathways (e.g. Dennig et al. 2015).

CHIPS contributes to closing this gap via two different novel approaches to quantify climate change impacts for different income groups, presented in this Deliverable. The first, presented in Section 1, builds on recent advances in quantifying economic damages from tropical cyclones (see Deliverable 2.2). It derives impacts of tropical cyclones in the United States on 5 different income groups, using historical data of exposure, vulnerability and damages. This approach could also be applied to other hazards and, depending on data availability, to other regions and is an important novel instrument to quantify adaptation options. The second, discussed in section 2, is a global empirical approach, assessing the effect of temperature on different income groups. Results from this work could be used to derive the income elasticity of aggregate climate impacts, a key parameter in the integrated assessment modeling of distributional effects of climate change impacts.

### 1. Income-specific vulnerability to tropical cyclones

Global disaster databases associate tropical cyclones (TCs) with the highest economic damages across meteorological and climatological extreme event categories (Guha-Sapir, 2023). Consequently, there is a large interest in TC impact models for risk assessments in contexts of insurance, policy, and climate change. Efforts to reproduce national reported damages have identified income-specific and regional vulnerabilities as an important impact channel (Eberenz et al. 2021, Geiger et al. 2016). However, on a sub-national level, the empirical work on differences in vulnerability to TCs is limited by the low availability of sub-national damage reporting. The empirical validation of approaches that use only national damage reporting to derive sub-national vulnerabilities is challenging (Baldwin et al., 2023).

In the CHIPS context, we undertook an analysis of the situation in the USA where county-level damage reporting is available (Storm Events Database version 3.1[1]) so that a validation of an income-specific sub-national model of vulnerability is possible (Haßel et al., in prep.). We used the impact modeling framework CLIMADA (Bresch and Aznar-Siguan 2020) to model economic damages associated with historical US hurricanes under two different assumptions on vulnerability: a nationally uniform (income-independent) and an income-specific vulnerability.

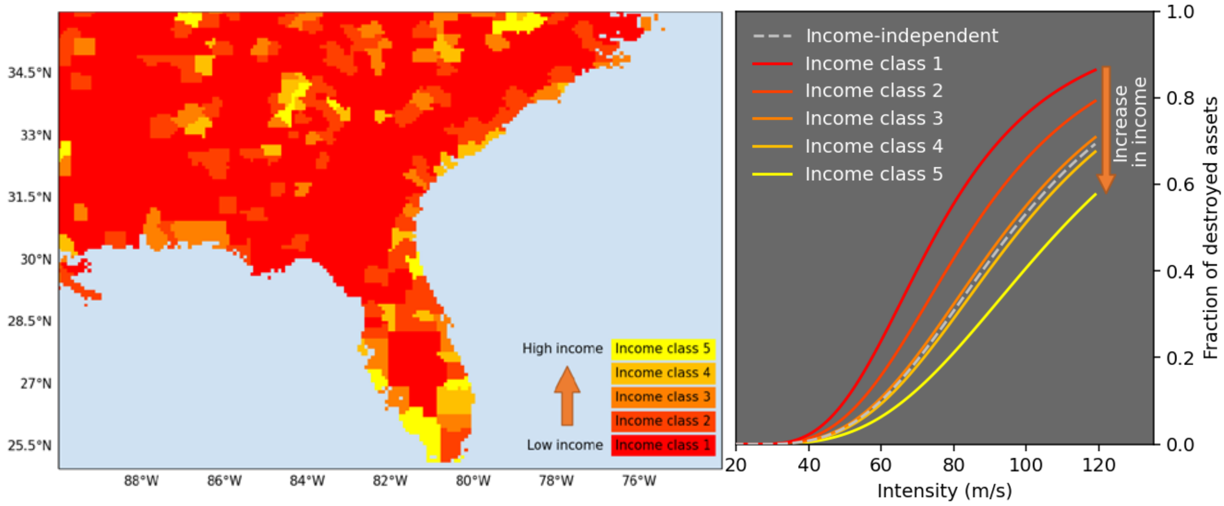


**Figure 1: Damage functions representing the vulnerability of five different groups of US counties**.
**Left:** The assignment of US counties to one of five income groups based on each county's per capita income.
**Right:** The proposed impact model uses damage reports on the county level to calibrate each group's vulnerability as the functional relationship between wind speed and exposed assets.

The impact model consists of gridded economic *exposure* and physical *hazard* data complemented by a functional relationship between hazard intensity and the share of destroyed assets in a grid cell, the *impact function* (Figure 1). In the context of this work, we interpret the impact function as an indicator of vulnerability: Higher vulnerability is associated with a steeper increase of the share of destroyed assets with hazard intensity.

National economic asset totals are downscaled using the LitPop-method (Eberenz et al. 2020) to a 10 km grid forming the exposure layer. The hazard layer consists of parametric hurricane wind fields (Eberenz et al. 2021, Holland 2008) that are generated from historical best track data (IBTrACS, Knapp et al. 2010). The vulnerability part of the impact model is then calibrated so that the modeled damages best reproduce the reports (Eberenz et al. 2021, Emanuel 2011). For the income-independent notion of vulnerability, a single function is fitted for the whole USA. For the income-specific notion of vulnerability, we first define five groups of counties according to their GDP per capita (extracted from US Census data). The income groups are defined in such a way that the national population is evenly distributed among the five groups, but the number and geographical area of counties belonging to each group is allowed to vary. A separate function is fitted for each of the five income groups of counties in order to define an income-specific notion of vulnerability.

[1] https://www.ncdc.noaa.gov/stormevents/

As our source for reported economic damages, we use the continuous record of storm events and associated economic damages on the county-level (Storm Events Database version 3.1) that is maintained by the US National Centers for Environmental Information (NCEI). Throughout the database, we were able to identify 3209 entries in the period 1996-2020 that are associated with a total of 97 hurricanes affecting 839 counties (37% of the US population). The hurricane-related damages amount to an average US$ 8.7 billion per year.

We find that the vulnerability of the poorer two income groups is significantly higher than the vulnerability of the richest income group while the vulnerability of the remaining two income groups is close to the income-independent vulnerability. We computed various indicators to give a quantitative impression of the difference in vulnerability (Figure 2):

1. If everyone in the USA was as vulnerable as the poorest (richest) income group, the total losses from the hurricanes covered by the reports would be more than 90% higher (40% lower) according to the impact model. This amounts to more than US$ 9 billion (4 billion) per year on average over 1996-2020.
2. Compared to an approach with an income-independent vulnerability, the income-specific model assigns 30% more (60% less) damages to the poorest (richest) income group, aggregated over all hurricanes covered by the reports.
3. Approximately 25% of the total reported damages (US$ 2.5 billion annually) could be avoided by increasing the resilience of the two poorer income groups to the level of the third income group while leaving the vulnerability of the other three income groups unchanged.

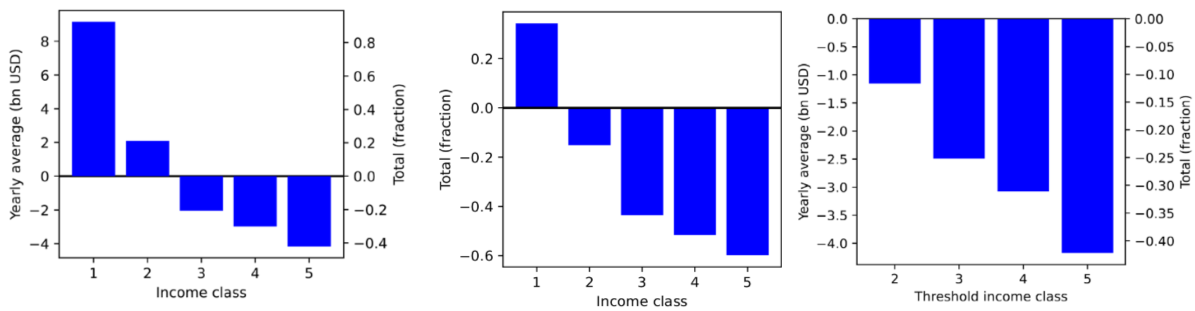


**Figure 2: Indicators that illustrate the difference in vulnerability between the five income groups of counties**. **Left:** The mean annual damage from hurricanes according to the proposed impact model under the assumption that everyone in the USA was as vulnerable as the first (second, third, fourth, fifth) income group. **Center:** The modeled mean annual damage suffered by each income group is compared to a model with an income-independent vulnerability. **Right:** The avoided damage from reducing the vulnerability of poorer income groups to the level of a threshold income group.

The income-specific approach not only allows to reproduce the historical damage records more accurately, and gives an impression of the unequal impacts that hurricanes have on different parts of the population within the USA, but it provides an estimate of the potential of adaptation efforts aiming at poorer parts of the population.

As part of the study, we also analyzed the model's potential to be applied to other world regions where data availability is not as good as in the USA, and to other historic and future periods. We found that the model works comparably well when replacing some of the input data with data that is globally available, such as a global gridded data set of GDP per capita. Furthermore, the TC wind hazard layer is available for other historic and future periods and for other world regions.

In a next step, the model could also be applied to estimate vulnerability in regions where only national damage reports are available (Baldwin et al., 2023). Other extreme event categories such as floods, heatwaves, or droughts could also be considered.

## 2. The link between temperature and economic growth for different income groups - a global empirical approach

Does climate change intensify within-country income inequality? Empirical evidence on within-country inequality has been relatively scanty and the limited findings from single country-level studies rather contentious. For instance, while the studies of Sedova et al., (2020) and Bui et al., (2014) show that climate-related shocks increase inequality, some studies (Abdullah et al. 2016; Keerthiratne & Tol, 2018; Little et al. 2006; Reardon & Taylor, 1996; Silva et al. 2015; Thiede, 2014; and Warr & Aung, 2019) have challenged this finding. At the global level, the effects of climate change on within-country inequality is poorly understood and very limited. Two recent studies (Paglialunga et al. 2022; Palagi et al. 2022) have tried to provide some answers, however, a major limitation of these two studies is the failure to incorporate detailed aspects of social heterogeneity or vulnerability. Although social, and political dynamics and conditions are important for the assessment of country-level inequality, a complementary global comprehensive approach is also important to be able to provide input to integrated assessment models (IAMs).

In recent years, IAMs have evolved from producing global and regional outcomes towards increasing geographic detail and the ability to quantify and project distributional effects and their complexities within countries (Rao et al. 2017), making the inclusion of within-country inequality and the distribution of climate impacts of great importance for future research (Baer 2009; Rao et al. 2017). In light of this, the goal of this study is to provide empirically-grounded impact estimates of climate change on income groups' specific income growth rates that can be used for IAMs. In this study, we used pre-tax national income from the World Inequality Database (WID) for 10 income groups and across 172 countries covering over 4 decades to estimate the impact of population-weighted temperature increases on income groups-specific income growth rates.

Our main identification strategy relies on observing how income growth is impacted by year-to-year fluctuations in country-level population-weighted temperature and precipitation. We employed a panel fixed-effects model to identify whether historical climatic variables affect the evolution of within-country income inequality, proxied by income groups' specific income growth rates. In the modelling framework, per-period growth rates of pre-tax national income were expressed as a nonlinear function of population-weighted temperature and precipitation. In the model, we controlled for all time-invariant differences between income groups through the inclusion of income group-specific fixed effects. Additionally, we controlled for abrupt global events, such as global recessions or shocks to energy markets that may affect income growth by including year-fixed effects. We also control for country-level trends and slowly evolving factors within countries such as evolving political institutions, demographic shifts, and trade liberalization that have consequences for income growth by including country-specific linear and quadratic time trends into the model. Because of the nonlinear specification of the model, we estimated the marginal effect of temperature to gain direct insights into the relationships between temperature and income growth. We also tested for the robustness of our main result by considering several model specifications, data sources, and income group configurations.

The results from our baseline model specification are shown in Table 1. The results suggest that temperature has a significant effect on the income growth of all income groups. The relationship between temperature and income growth is nonlinear with income growth being maximized at relatively higher temperatures for the bottom 20% and the top 10% of the income distribution. Figure 3, shows the plot of the marginal effect of a 1°C increase in population-weighted mean annual temperature on income growth (y-axis) for the bottom 10% and top 10% of the income distribution conditional on the annual average population-weighted temperature in a country (x-axis). The results show positive marginal effects at the lower end of the temperature spectrum and negative marginal effects at the higher end of the temperature spectrum. For each income group, we find that the mean marginal effect is positive at temperatures below the estimated temperature optima, and negative thereafter.

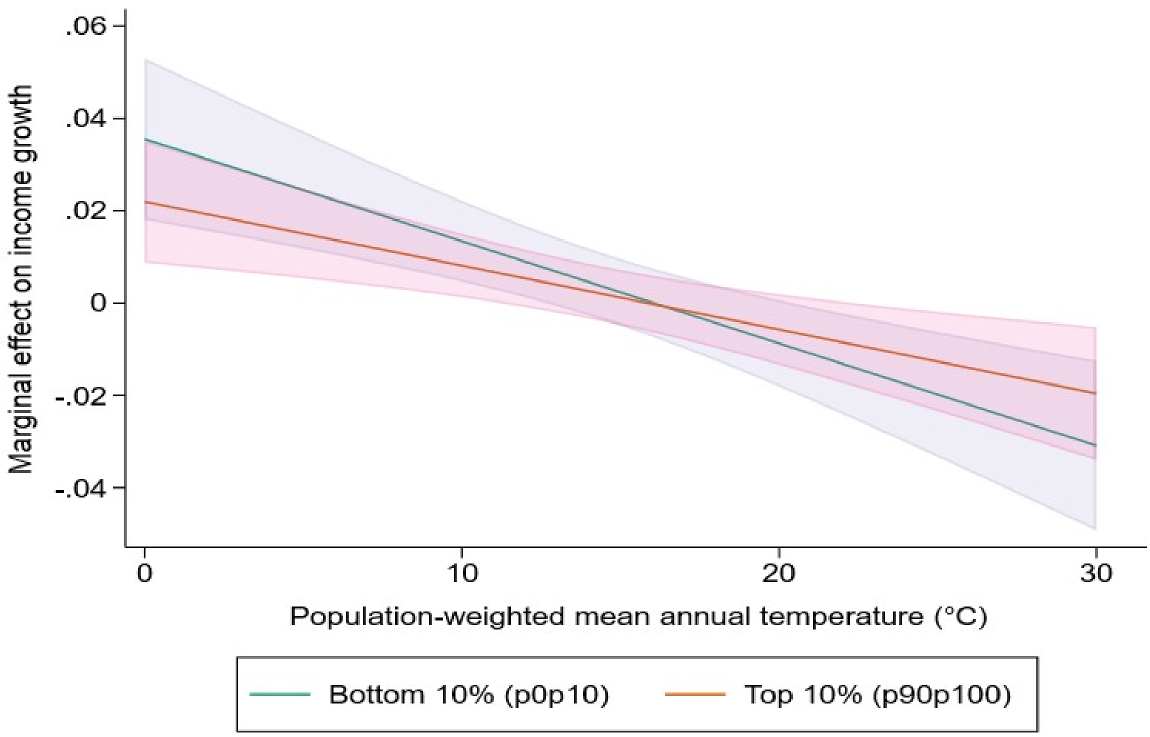


**Figure 3: Marginal effects of population-weighted mean annual temperature on income groups' specific income growth rates**. The figure shows the marginal effects of a 1°C increase in population-weighted mean annual temperature on income growth rates of the bottom 10% and top 10% of the income distribution, as estimated in equation [3]. The grey and pink shaded regions show the 95% confidence interval for marginal effects estimates for the bottom 10% and top 10% of the income distribution respectively.

Because low-income groups are more vulnerable to temperature changes due to occupation-related exposure, we find that in Figure 3, the mean marginal effect is positive and larger at temperatures below the estimated temperature optima (see Table 1) compared to the top 10% of the income distribution. However, beyond the estimated temperature optima, they suffer greater marginal losses (reductions in income growth) per 1°C increase in mean annual temperature compared to the top 10% of the income distribution.

Using the global relationship for each income group estimated from equation [1] and shown in Table 1, Figure 4 shows the country-level estimates of the effect 1°C increase in country-level mean annual temperature on income growth rates for the bottom 10% and top 10% of the income distribution in percentage points. The results in Figure 4 show geographical variations of impacts. The reduction of income growth per 1°C increase in country-level mean annual temperature is larger for the bottom 10% of the income distribution in climatologically warmer countries, implying a strong latitudinal dependence.

**Table 1: Results of the main econometric specification for the effect of temperature on income groups-specific income growth rates**

| Variables | p0p10 | p10p20 | p20p30 | p30p40 | p40p50 | p50p60 | p60p70 | p70p80 | p80p90 | p90p100 |
|---|---|---|---|---|---|---|---|---|---|---|
| T | 0.0355*** | 0.0286*** | 0.0238*** | 0.0227*** | 0.0220*** | 0.0225*** | 0.0220*** | 0.0212*** | 0.0208*** | 0.0220*** |
| | (0.0089) | (0.0070) | (0.0060) | (0.0060) | (0.0060) | (0.0060) | (0.0060) | (0.0060) | (0.0061) | (0.0067) |
| $T^2$ | -0.0011*** | -0.0009*** | -0.0008*** | -0.0008*** | -0.0008*** | -0.0008*** | -0.0008*** | -0.0007*** | -0.0007*** | -0.0007*** |
| | (0.0003) | (0.0002) | (0.0002) | (0.0002) | (0.0002) | (0.0002) | (0.0002) | (0.0002) | (0.0002) | (0.0002) |
| P | 0.0268 | 0.0300* | 0.0260* | 0.0267* | 0.0295** | 0.0314** | 0.0324** | 0.0335** | 0.0346** | 0.0396*** |
| | (0.0234) | (0.0172) | (0.0156) | (0.0149) | (0.0145) | (0.0143) | (0.0141) | (0.0140) | (0.0140) | (0.0145) |
| $P^2$ | -0.0078 | -0.0083* | -0.0072* | -0.0076* | -0.0083** | -0.0087** | -0.0090** | -0.0093** | -0.0097** | -0.0106*** |
| | (0.0057) | (0.0047) | (0.0043) | (0.0041) | (0.0040) | (0.0040) | (0.0040) | (0.0040) | (0.0039) | (0.0040) |
| Constant | -17.4432*** | -15.5586*** | -15.1138*** | -14.8473*** | -14.8353*** | -14.6603*** | -14.5140*** | -14.2873*** | -14.1780*** | -14.2006*** |
| | (0.2687) | (0.2251) | (0.2226) | (0.2217) | (0.2198) | (0.2158) | (0.2140) | (0.2133) | (0.2135) | (0.2212) |
| Observations | 7,051 | 7,051 | 7,051 | 7,051 | 7,051 | 7,051 | 7,051 | 7,051 | 7,051 | 7,051 |
| $R^2$ | 0.0708 | 0.1024 | 0.1113 | 0.1134 | 0.1156 | 0.1164 | 0.1160 | 0.1160 | 0.1157 | 0.1180 |
| Countries | 172 | 172 | 172 | 172 | 172 | 172 | 172 | 172 | 172 | 172 |
| Income group FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Linear trend | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Quadratic trend | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Optimum | 16.0496 | 15.6445 | 14.6339 | 14.5735 | 14.3467 | 14.4985 | 14.3588 | 14.2983 | 14.2183 | 15.8521 |
| ME at 10°C | 0.0134*** | 0.0103*** | 0.0075** | 0.0071** | 0.0067** | 0.0070** | 0.0067** | 0.0064** | 0.0062* | 0.0081** |
| | (0.0044) | (0.0037) | (0.0033) | (0.0033) | (0.0033) | (0.0032) | (0.0032) | (0.0032) | (0.0032) | (0.0035) |
| ME at 25°C | -0.0198*** | -0.0171*** | -0.0168*** | -0.0163*** | -0.0163*** | -0.0163*** | -0.0163*** | -0.0159*** | -0.0158*** | -0.0127** |
| | (0.0069) | (0.0059) | (0.0055) | (0.0053) | (0.0053) | (0.0052) | (0.0052) | (0.0052) | (0.0053) | (0.0055) |
| Adj. $R^2$ | 0.0169 | 0.0503 | 0.0597 | 0.0619 | 0.0642 | 0.0650 | 0.0646 | 0.0647 | 0.0643 | 0.0668 |

∗∗∗, ∗∗, ∗ represent 1%, 5%, and 10% significance levels, respectively. Standard errors are shown in parentheses and clustered at the country and income group level.

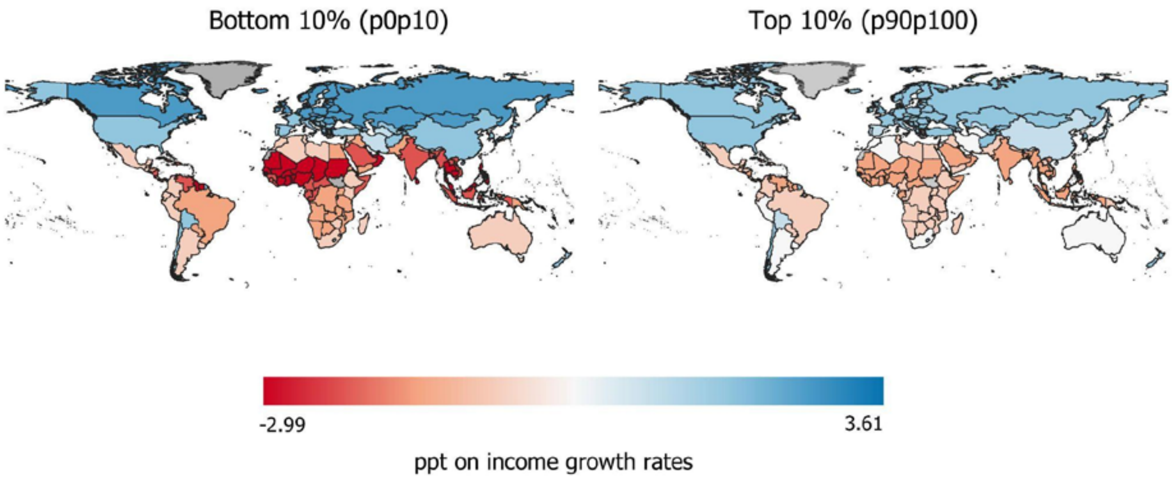


**Figure 4:** Reduction in income growth rates per 1°C increase in mean country-level temperature. The reduction is larger for income groups in countries accustomed to a higher temperature, implying a strong latitudinal dependence. Marginal effects reported here are estimated from the baseline model in equation [1]. Red denotes reductions in income growth per 1°C increase in mean temperature whereas blue indicates income growth gains. The left panel shows the marginal gains and losses of income growth for the bottom 10% of the income distribution while the right panel is for the top 10% of the income distribution.

## 3. Estimating income elasticities of climate damages from spatial heterogeneity in damages

Households with different income levels may face different levels of climate damages because of their different exposure to the risk. One strategy to estimate the income elasticity of climate damages is therefore to use geographical differences in climate impacts at the subnational level. The question is then whether poorer areas are also subject to more damages (see for instance Burke and Tanutama, 2019) even if they are in regions with similar climates. In particular, we can test within a country if poorer regions are more impacted by climate damages using data on subnational economic output at the district level.

We have adopted this strategy to calibrate the income elasticity in the NICE model (Gilli, 2022). To do so, data from DOSE dataset (assembled by Kalkuhl, Wenz and Kotz, 2021) have been matched with weather data *from the Inter-sectoral Impact Model Intercomparison Project (ISIMIP)*. We have computed future regional damages using a regression relating local temperature increase to local output loss (see Gilli, 2022).

In the NICE model, the distribution of damages for different income levels (within a region) is done using the formula:

$$\boldsymbol{d_{ic} = \kappa \cdot q_{ic}^{\xi}}$$

where $\boldsymbol{d_{ic}} = \frac{\boldsymbol{D_{ic}}}{\boldsymbol{D_c}}$, is the share of country's damages that affect income group i ($\boldsymbol{D_c}$ are total damages in country c, $\boldsymbol{D_{ic}}$ are total damages in income group i of country c), and $\boldsymbol{q_{ic}} = \frac{\boldsymbol{Y_{ic}}}{\boldsymbol{Y_c}}$ is the income share of income group i ($\boldsymbol{Y_c}$ is total income in country c, $\boldsymbol{Y_{ic}}$ is total income in income group i of country c). Taking the logarithm of the expression, the equation can be written in the following way:

$$\boldsymbol{ln}\left(\frac{\boldsymbol{s_{ic}}}{\boldsymbol{s_c}}\right) = \boldsymbol{\alpha} + \boldsymbol{\eta} \cdot \boldsymbol{ln}(\boldsymbol{q_{ic}}), \qquad (1)$$

with $\boldsymbol{s_{ic}} = \frac{D_{ic}}{Y_{ic}}$ and $\boldsymbol{s_c} = \frac{D_c}{Y_c}$ the respective shares of damages in the income group and in the country as a whole, and $\boldsymbol{\eta} = \boldsymbol{\xi} - \boldsymbol{1}$.

Rather than income groups, we use subnational regions and computed future damages (for a 2°C average global temperature increase). So, we can estimate equation (1). The result is in Table 2 below.

**Table 1: Results of the regression in Equation (1) relating relative shares of damages to relative income**

| | **Values** |
|---|---|
| $\boldsymbol{\alpha}$ | -3.454***<br>(0.045) |
| $\boldsymbol{\eta}$ | -0.158***<br>(0.033) |
| Implied value for $\boldsymbol{\xi}$ | 0.842 |

$***$ represents a 1% significance level. Standard errors are shown in parentheses.

We thus obtain a value of the income elasticity below 1. It means that when income increases by 1%, damages increase by less than 1% (specifically by only 0.85%). Climate damages thus have a regressive impact: they bear more on poorer people and increase existing inequalities.

## 4. Conclusions

These very different approaches constitute each an important methodological step forward with regards to quantifying distributional impacts of climate change. The first constitutes a prototype study combining modeling results with data which could be applied also to other regions and hazards. With its focus on vulnerability it allows a direct relation to adaptation policies which is of increasing importance to policy makers and decision makers in countries and communities in the future. Finally, it also illustrates the losses and vulnerabilities in a high-income country despite its overall low vulnerability and the small impact each tropical cyclone has on the country's GDP as a usual measure of climate impacts.

The second approach is designed to allow the derivation of the income elasticity of climate damages based on the differential impacts on income groups. This parameter is of crucial importance for the inclusion of inequality in integrated assessment modeling (see Deliverable 5.2) and is so far not quantified robustly. This would be the next step in the analysis of these results.

Both analyses will be published in the near future (Haßel et al, in prep. and Collins-Sowah et al., in prep.).

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## Acknowledgement

The project CHIPS is part of AXIS, an ERA-NET initiated by JPI Climate, and funded by FORMAS (SE), DLR/BMBF (DE, Grant No. 01LS1904A), AEI (ES) and ANR (FR) with co-funding by the European Union (Grant No. 776608).