

Impact attribution of climate and population change on compound flood impacts from tropical cyclone Idai in Mozambique

Doris M. Vertegaal

doris.vertegaal@deltares.nl

Deltares, Delft, the Netherlands; Institute for Environmental Studies (IVM), Vrije Universiteit Amsterdam, Amsterdam, the Netherlands

Bart J. J. M. van den Hurk

Deltares, Delft, the Netherlands; Institute for Environmental Studies (IVM), Vrije Universiteit Amsterdam, Amsterdam, the Netherlands

Anaïs Couasnon

Deltares, Delft, the Netherlands; Institute for Environmental Studies (IVM), Vrije Universiteit Amsterdam, Amsterdam, the Netherlands

Dominik Paprotny

Institute of Marine and Environmental Sciences, University of Szczecin, Poland; Potsdam Institute for Climate Impact Research (PIK), Member of the Leibniz Association, Potsdam, Germany; Baltic Climate Centre, University of Szczecin, Poland

Sanne Muis

Deltares, Delft, the Netherlands; Institute for Environmental Studies (IVM), Vrije Universiteit Amsterdam, Amsterdam, the Netherlands

Article

Keywords: Climate change, population change, impact attribution, tropical cyclone, compound flooding

Posted Date: June 29th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-9827678/v1>

License:   This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Additional Declarations: No competing interests reported.

Abstract

Impacts of extreme weather events are usually a complex interplay of compounding socio-economic and climatic drivers. In this paper, we attribute the effect of climate and population change on the number of people exposed to flooding from tropical cyclone (TC) Idai, making landfall in Mozambique in 2019. We apply an extended storyline attribution framework based on a globally-applicable model chain to simulate compound flooding and its impacts under factual and counterfactual climate and population conditions. This enables impact attribution to both drivers, and disaggregation of the results across different flood depth categories and socio-economic groups. Both climate and population change since 1975 have increased the number of people exposed to flooding from TC Idai, with population change being the dominant driver. Climate change increases the flood extent and flood depth, whereas population change alters the number of people living in the flooded area. These drivers together change the distribution of people exposed to flooding, leading to different attribution assessments per flood depth category. Moreover, we exemplify that climate change impacts are unevenly distributed across socio-economic groups. Spatial aggregation of the impact attribution assessment therefore has the potential to mask the disproportionate effects of climate change on particularly vulnerable socio-economic groups.

Introduction

Human-induced climate change alters the intensity and frequency of extreme weather events worldwide¹. The impacts of extreme events are shaped by multiple interacting drivers, including climate change and socio-economic factors^{2–9}. Relevant socio-economic drivers include urbanization and land cover change, population and economic growth, and other developments such as flood adaptation, early warning and preparedness. These drivers can be very dynamic and interact with the impact of extreme events on different spatial and temporal scales^{10–13}. For example, historical flood impacts in Europe have been exacerbated by population and economic value growth but largely dampened by better risk management and reduced flood vulnerability¹⁴.

Impact attribution can be used to quantify the relative contributions of (multiple) extreme event impact drivers¹³. Where previously impact attribution studies focussed primarily on assessing the effect of climate change alone^{15,16}, methodologies are expanding to include socio-economic drivers¹⁴. Addressing how socio-economic drivers, such as land use change and economic development, contributed to the impacts of an extreme weather event provides context for the role of climate change. There are various event-based attribution studies that consider the effect of socio-economic drivers on the hazard of the event^{17–19}, all concluding that such drivers have major relevance. However, these studies do not propagate the effect of socio-economic drivers to impact or account for associated changes in exposure and vulnerability. A multi-driver attribution framework that propagates the effect of both climate and non-climatic drivers to impacts therefore remains underdeveloped, particularly in data-scarce regions.

Extreme event impacts, and how these might be altered by climate and socio-economic drivers, are not equally distributed among society^{20–24}. Low-income countries are disproportionately impacted by climate change²⁵ and are also projected to experience a larger increase in exposure in the coming decades²⁶, potentially resulting in amplified impacts. At subnational level, low-income households face greater exposure to flood risk^{26–28}. Attribution statements based on aggregated estimates of climate change impacts, such as a 13 % increase in flood damages²⁹, do not capture how those impacts are distributed among society or how different drivers shape that distribution. Attribution assessments disaggregated by socio-economic and hazard characteristics can better capture the unequal distribution of impacts across society.

In this study, we address this research gap for the case of Tropical Cyclone (TC) Idai, hitting Mozambique in 2019. Idai made landfall close to the city of Beira, located in the Sofala province, and was one of the most destructive cyclones to make landfall in the Southern Hemisphere. The cyclone caused strong winds (> 150 km/h), widespread flooding driven by heavy rainfall of more than 600 mm (more than half the annual rainfall³⁰) and a storm surge height of 2.5 to 4.5 m occurring close to neap tide^{31,32}. Mozambique is a highly vulnerable country with vast inequalities among society and ongoing crises at the time of the cyclone, which all contributed to turning the event into a disaster³³. In Mozambique alone, TC Idai caused more than 600 fatalities and affected 1.85 million people³⁴. The exponential population growth in recent decades³⁵ is likely to have confounded a change in climate conditions determining Idai's societal impacts. Existing impact attribution studies of TC Idai have not yet attributed the effect of socio-economic drivers in addition to that of climate change^{36,37}, nor do they disaggregate the attribution assessment.

We build on the storyline attribution framework of Vertegaal et al.³⁷, which uses a globally applicable state-of-the-art model chain to simulate compound flooding and its impacts under factual and counterfactual climate conditions. We expand this framework in three ways: first, by introducing counterfactual exposure conditions to attribute the contribution of population change alongside that of climate change since 1975; second, by disaggregating the attribution assessment by flood inundation depth; and third, by disaggregating the attribution assessment across socio-economic groups.

Methods

The storyline attribution framework considers factual and counterfactual (alternative conditions) scenarios for flood hazard and flood exposure (Fig. 1). The factual and counterfactual flood hazard scenarios are based on Vertegaal et al.³⁷ and present the simulated compound flooding from TC Idai under both the observed climate conditions and with the climate trend removed until the counterfactual baseline of 1975. The factual and counterfactual exposure scenarios are based on the Global Human Settlement Layer population datasets^{38,39} for 2020 (the closest year available to TC Idai in 2019), and for 1975 as a counterfactual baseline. The exposed population, i.e. the number of people within the flooded

area, is used as impact metric, which is disaggregated both per flood depth category and per socio-economic characteristic of the population.

Scenarios for attribution

We make use of four scenarios to disentangle the plausible relative contributions of climate change and population change, as well as their combined effect (Table 1). The exposed population for the different scenarios is estimated by overlaying the population raster with the simulated compound flooding from TC Idai, as described in the following sections. As counterfactual baseline, we use 1975 to study changes within the timeframe of a single human generation of the society that lives today.

Table 1
Overview of factual and counterfactual scenarios.

Scenario	Description
Factual	Climate conditions during TC Idai in 2019 and population of 2020
Counterfactual climate	Removed climate trend since 1975 for rain, wind and SLR
Counterfactual population	Population of 1975
Counterfactual climate + population	Climate trend removal of rain, wind and SLR and population of 1975
Flood hazard	

The hydrodynamic modelling chain of Vertegaal et al.³⁷ used to simulate compound flooding from TC Idai consists of the reduced-complexity compound flood model Super-Fast INundation of CoastS (SFINCS)⁴¹, with coastal boundary conditions of tide, surge and nearshore wave setup from the hydrodynamic model D-Flow FM from the Delft3D Flexible Mesh Suite⁴² combined with SnapWave⁴³, and discharge boundary conditions from the hydrological model wflow⁴⁴. For more details on the modelling chain and validation, we refer to Vertegaal et al.³⁷. The flood maps are generated at 25 m resolution, and masked for permanent water using the Global Surface Water dataset⁴⁵. We only consider flood depths $\geq$ 0.15 m, indicative for exposure levels associated with negative consequences for society⁴⁶. The flood maps are used to estimate the exposed population.

For the factual flood hazard scenario, the meteorological forcing is a combination of the ERA5 reanalysis dataset⁴⁷ and the IBTrACS best track TC data^{48,49}. This simulation was validated against available observations and shown to reasonably represent observed flood conditions³⁷. For the counterfactual climate scenario, the meteorological forcing and boundary conditions are adjusted to represent plausible climate conditions accounting for substantially reduced levels of climate change back in 1975. We do this by removing the long-term climate trend from TC flood drivers for which there is scientific consensus to be affected by climate change⁵⁰. We use a moderate climate change adjustment of key flood drivers representing the counterfactual baseline year of 1975 (see supplementary Table S1), which

corresponds to a 6 % reduction in TC rainfall, a 4 % reduction in TC maximum wind speed, and a removal of 7 cm SLR.

Flood exposure

We make use of a gridded population dataset from the Global Human Settlement Layer^{38,39} at 100 m spatial resolution and 5-year temporal resolution, available from 1975 to 2030. We downscale the population raster to the resolution of the flood map (25 m) by evenly distributing the population within the ~ 100 m grid cell to the available land cells within that grid cell.

For the factual population scenario, we use the population raster of 2020, the closest year available to that of TC Idai in 2019. For the counterfactual population scenario, we use the population raster of 1975, the baseline year. Population growth between 1975 and 2020 has not been spatially homogeneous. To test the potential impact of changes in population density patterns, a sensitivity experiment has been conducted with a spatially uniform population growth scenario since 1975, retaining the total population growth.

To calculate the population exposed to flooding (the prime flood impact indicator), the population raster is overlaid with the flood map for flood depths ≥ 0.15 m. The entire population located within the flooded area is considered to be exposed. Population values are reported as number of people rounded to the nearest thousand for presentation purposes. The total and exposed population for the factual scenario are validated against reported affected populations (see supplementary information, Tables S2 and S3, and Fig. S1). The total population shows good agreement at the case study scale (mean relative error of 1%), with larger differences at sub-district level (range - 14% - 19%). Generally, we underestimate exposed population, with an overall reasonable agreement for Beira (mean relative error 17%) but lower agreement for the other districts. The change in exposed population attributable to climate change and/or population change is defined as the relative change in exposed population between the counterfactual and factual scenario, expressed as:

$$A (\%) = \frac{F-CF}{F} * 100 \% (1),$$

where A is the attributable change in %, F is the exposed population from the factual scenario and CF from the counterfactual scenario.

Attribution disaggregation

We disaggregate the results by flood inundation depth (carried out for both climate and population counterfactuals), and by socio-economic characteristics of the exposed population (for climate counterfactual only, as no dataset exists for counterfactual socio-economic conditions in 1975). The attributable exposed population for the disaggregated assessment represents the relative change per category or group.

For the flood depth disaggregation, we consider three flood depth categories: low (0.15 m – 0.5 m), moderate-to-high (0.5 m – 1.5 m), and very high (> 1.5 m). These thresholds are defined based on relevant literature^{9,46}. Low flood depths can cause economic and livelihood disruptions. Moderate-to-high flood depths can cause a substantial part of the exposed population to face risk to life and severe economic and livelihood disruptions. Very high flood depths of more than 1.5 m pose a substantial risk to life to most of the exposed population and long-lasting livelihood disruptions.

For the socio-economic disaggregation, we consider relevant population characteristics, which include the population's wealth, settlement type (urban or rural), age, sex, education level¹¹, and household size. The latter is relevant as members of larger households can support each other under severe conditions, thereby increasing their coping capacity. We differentiate between more and less vulnerable groups, which is relative to the rest of the country. We assume that more vulnerable groups are generally poorer (relative to the country), not or poorly educated (less than complete secondary level)^{13,51}, living in rural areas⁵², infants or elderly people (< 5 or above 65 years old)^{53,54}, female⁵¹, and living alone^{55,56}. We assume that less vulnerable people are generally richer (relative to the country), higher educated (above tertiary level), living in urban areas, between 5 and 64 years old, male, and living in a household of at least two people. For simplicity, we consider each of these characteristics independently.

The gridded socio-economic population data is taken from a global dataset for 2015 developed by Ton et al.^{57,58} at a 1 km spatial resolution. Similar to the population data, we downscale the socio-economic data to the flood raster resolution to calculate the exposed population per socio-economic group. Since the data is available for a single year only, we do not account for temporal variations. The largest uncertainty in this global dataset stems from the lack of country specific data for Mozambique⁵⁹. The data is based on socio-economic population data from the three geographically nearest countries with a similar human development index as that of Mozambique. We find reasonable agreement between the estimated socio-economic population characteristics and reported subnational socio-economic data for the Sofala province from the Instituto Nacional de Estatística (INE) in Mozambique⁶⁰ (see supplementary Table S4).

Results

Using the storyline attribution framework, we quantify the separate and combined contributions of climate change and population change since 1975 to the population exposed to compound flooding from TC Idai. We disaggregate these attribution assessments per flood depth category and socio-economic characteristics of the population.

Attributable flood impact to climate and population change

The population exposed to compound flooding from TC Idai is reduced substantially when reverting to 1975 climate and population conditions (Figs. 2 and 3). In our factual scenario, around 250,000 people are estimated to be exposed to compound flooding from TC Idai (Fig. 2, panel a), which is 27% of the

total population living in the case study area at the time of the event. Aggregating over the case study area, the flood extent increases by 2% due to climate change (Fig. 2, panel b), whereas the total population increases with 204% (Fig. 2, panel c). The factual flood and population conditions, and their changes since 1975, can be found in the supplementary Fig. S2.

The fraction of the exposed population attributable to climate change is 9% (Fig. 3, panel a, supplementary Table S5), compared to 80% that can be attributed to population change (Fig. 3, panel b). Climate change and population change combined further exacerbate the exposed population, accounting for an attributable fraction of 84% (Fig. 3, panel c). The separate effects of climate change and population change are not additive, as their combined effect is less than the sum. This is the result of population change in areas that only flood as a result of climate change. When considering absolute numbers, the largest change occurs in the Beira municipality with ~ 19,000 people additionally exposed due to climate change compared to ~ 180,000 people additionally exposed due to population change. In the densely populated city of Beira, a small change in flood extent affects a high number of people, exacerbated by high population growth (300%).

Disaggregated attributable flood impact

Attribution per flood depth category

Our results show that climate change and population change alter the exposed population distribution across flood depth categories (Fig. 4, supplementary Table S5). In the factual scenario, flood depth categories are generally very high in the flood plains of the major Buzi and Pungwe rivers, and low and moderate-to-high in the Beira area (Fig. 4, panel a). Climate change mostly increases flood depth categories from moderate-to-high to very high in rural areas, and from low to moderate-to-high in urban areas such as Beira (Fig. 4, panel b). However, despite the stronger categorical shift in rural areas, higher population density in urban areas results in a larger number of people being exposed to very high flood depths in urban settings (see supplementary Table S6).

In general, the fraction of the exposed population attributable to climate change increases with flood depth category (Fig. 4, panel c). For low flood depths, 3% of the exposed population is attributable to climate change (3,000 people, supplementary Fig. S3 and Table S5), compared to 13% (15,000 people) for moderate-to-high flood depths. For most people exposed to moderate-to-high flood depths, the flood depth increases by 11 cm (from 1.10 m to 1.21 m; supplementary Fig. S4). The relative contribution of climate change is greatest at very high flood depths (24%). However, the largest absolute contribution is found at moderate-to-high flood depths (15,000 people), compared to 4,000 people at very high and 3,000 people at low flood depths.

Population change accounts for the largest attributable fraction of the exposed population in the moderate-to-high flood depth category. In this category, 89% (104,000 people) of the exposed population can be attributed to population change (Fig. 4, panel c, and supplementary Table S5). At low and very high flood depths, 74% (87,000 people) and 63% (10,000 people) can be attributed to population change,

respectively. This implies that relatively more people moved into moderate-to-high flood depth zones, compared to low and very high flood depth zones (see supplementary Fig. S5).

Across all flood depth categories, the largest fraction of the exposed population is attributable to the combined effect of climate and population change. This fraction is 78% (92,000 people) at low flood depths, 91% (107,000 people) at moderate-to-high flood depths, and 67% (106,000 people) at very high flood depths.

Climate change alters the flood extent and flood depth distribution, whereas population change alters the distribution of people within the flooded area. These drivers together change the distribution of people exposed to flooding, leading to different attribution assessments per flood depth category. Using a discrete impact classification (low, moderate-to-high, very high flood depth category) instead of binary impact classification (exposed or not exposed) reveals that the largest population change occurs at moderate-to-high flood depth categories, compared to low and very high flood depth categories. This analysis shows the sensitivity of using a binary classification when attributing changes based on flood extent only.

Attribution per socio-economic group

Figure 5 shows the disproportionate climate change effects between groups with different socio-economic characteristics (i.e. wealth, settlement type, age, sex, education and household size). When considering a binary (exposed or not exposed) instead of discrete (low, moderate-to-high, very high flood depth category) impact classification, the attributable fraction of the exposed population is generally higher for less vulnerable people (richer and more educated), as opposed to more vulnerable people (poorer and less educated). However, when disaggregating per flood depth category, the attributable fraction at very high flood depths is generally higher for more vulnerable than for less vulnerable people. Across most socio-economic characteristics, climate change alters flood impacts disproportionately, which is masked when using a binary rather than discrete classification.

The disproportional effects of climate change across socio-economic groups can be linked to the urban–rural population distribution (see supplementary Fig. S6 and Table S7). There is a clear urban–rural segregation for levels of wealth and education, whereas sex, household size, and age exhibit little to no spatial differentiation across settlement types. Poorer groups constitute 36% of the rural population but only 4% of the urban population, whereas richer groups make up 91% of the urban population but only 32% of the rural population. A similar pattern is observed for education, with lower-educated groups overrepresented in rural areas (85% vs. 52% in urban areas), and higher-educated groups concentrated in urban areas (24% vs. 3% in rural areas).

In densely inhabited urban areas, a small change in flood extent, regardless of flood depth, can lead to a large increase in number of exposed people, explaining the larger attributable fraction for less vulnerable groups when impacts are aggregated across flood depth categories. In sparsely inhabited rural areas, climate change mostly pushes the flood depth category from moderate-to-high to very high (Fig. 4, panel

b), thus affecting the dominantly more vulnerable population living in these areas. When considering absolute numbers, the attributable fraction per socio-economic group reflects the socio-economic distribution; groups with a larger population show higher absolute attributable fraction than those with a smaller population (see supplementary Fig. S7). From this analysis, we conclude that climate change disproportionately affects different socio-economic groups, and that its detection depends on the level of aggregation of model outputs and on whether absolute or relative attributable fractions of the exposed population are used.

Discussion

Implications of impact attribution of compound flooding

In this study, we find that both population change and climate change since 1975 have increased the number of people exposed to flooding from TC Idai. Of these drivers, 80% of the exposed population is attributable to population change and 9% to climate change. Climate and population change combined account for 84% of the exposed population. The attribution assessment is sensitive to whether the exposed population is aggregated or disaggregated across flood depth categories and socio-economic characteristics. Similar sensitivities have been reported in previous studies, which show that spatial disaggregation of flood impacts can lead to stronger⁶¹ and more variable⁹ climate signals. These findings highlight the importance of moving beyond a binary impact classification to account for changes in flood depth distribution, which better captures the relationship between hazard magnitude and impact severity⁶² and therefore has the potential to provide more relevant information for risk management.

In the future, the population exposed to flooding in Mozambique is projected to increase further as the result of ongoing climate change and population change, with population change remaining the dominant driver^{26,63}. Before 2050, the population of Mozambique is expected to double compared to 2019³⁵, which together with ongoing urbanisation, land subsidence in coastal areas, and climate change, is projected to increase future flood risk⁶³. Globally, the largest projected increase in exposed population is found for coastal-fluvial transition regions in Africa, for which Beira is an illustrative example²⁶. Overall, this suggests that managing future flood risk in Mozambique requires integrating both socio-economic change and climate change impacts.

Limitations and future directions

A limitation of our work is the relatively coarse spatial and temporal resolution of the underlying population and socio-economic datasets. Higher spatial and temporal resolution of socio-economic data is required to accurately contextualize the disproportionate impacts of climate change among different socio-economic groups. The global spatially disaggregated socio-economic data from GLOPOP-SG^{57,58}, is only available for 2015. While assuming similar socio-economic characteristics between 2015 and

2019 for TC Idai is reasonable, this means that the dataset will become increasingly outdated for more recent events. More importantly, the socio-economic data for Mozambique is based on data from three geographically nearby countries with a similar Human Development Index (HDI). Country-specific socio-economic data would strengthen confidence in attributing the effect of climate change between socio-economic groups at suburban level. For example, while not evident from our analysis, vulnerable people living in flood-prone informal settlements in Beira are found to be disproportionately impacted by flood events^{64–66}. To improve our understanding of how climate and population change affect inequality in flood exposure in Mozambique, more socio-economic characteristics, such as illiteracy, unemployment or disability status⁶⁷, should be considered as well as their intersectionality^{51,68}.

Emerging mixed-method approaches that combine quantitative storyline attribution with qualitative causal analysis offer a promising avenue for capturing indirect socio-economic drivers and non-quantifiable impacts. Such approaches can help trace the underlying socio-economic processes contributing to increased risk⁶⁹, as illustrated by Webb et al.⁷⁰. Their study shows how the increase in flooding during TC Idai associated with deforestation can be traced back to charcoal production in rural areas of the Buzi and Pungwe basins, which serves as a last-resort livelihood strategy for populations living in persistent poverty following previous disasters. In our case, a mixed-method approach could help explore whether population growth is partly offset by concurrent changes in vulnerability factors such as disaster management, socio-economic development, and adaptation levels⁷¹. Accounting for such dynamics may change estimates of population exposure that can be attributed to population change, and improve insight into changing flood risk drivers under climate change.

Conclusion

Our study disentangles the effect of climate change and population change since 1975 on the population exposed to flooding from TC Idai in Mozambique by expanding the globally applicable storyline attribution framework of Vertegaal et al.³⁷. We find that 84 % of the population exposed to flooding from TC Idai is attributable to the combined effect of population and climate change. This is primarily driven by population change, with 80 % of the exposed population attributable to population change alone, compared to 9 % attributable to climate change alone. Climate change alters the flood depth distribution whereas population change alters the distribution of people within the flood plain. These drivers together change the distribution of people exposed to flooding, leading to different attribution assessments per flood depth category. In the case of TC Idai, the fraction of the exposed population attributable to climate change increases with flood depth category, whereas population change is the dominant driver across all flood depth categories and contributes most to the number of people exposed in the moderate-to-high flood depth category.

Disaggregating the attribution results across socio-economic groups reveals that the effect of climate change is unevenly distributed across society. Climate change has a larger effect on shifting the flood depth category from moderate-to-high to very high in sparsely inhabited rural areas, compared to densely

inhabited areas where flood depths tends to be low to moderate-to-high. This translates to disproportionate impacts of climate change across socio-economic groups, where more vulnerable people, more likely to live in rural areas, are disproportionately exposed to very high flood depths compared to less vulnerable urban populations. This outcome is masked when considering a binary instead of discrete impact classification. Which drivers and metrics to include, and how to disaggregate the attribution assessment, should ultimately be policy informed to develop purpose-driven attribution statements.

Declarations

Competing interests

The authors declare that they have no conflict of interest.

Funding

This research was done as part of the “Compound extremes attribution of climate change: Towards an operational service” (COMPASS) project, which is funded by the European Union’s HORIZON Research and Innovation Actions Programme under Grant Agreement No. 101135481.

Author Contribution

DV, BvdH, AC, DP, and SM conceived the idea for this study, jointly designed the experiments, and interpreted initial results. DV executed the experiments and set up the adjust climate counterfactual and executed the model-chain as part of storyline attribution framework. DV conducted the computational processing and analysis of results. DV wrote the manuscript with input from BvdH, AC, DP, and SM.

Acknowledgement

We would like to thank Ted Buskop and Toon Haer for pointing us at the socio-economic data of Ton et al., and Jens de Bruijn for sharing the spatially disaggregated data of Ton et al. We would also like to thank Izidine Pinto for sharing his perspectives on the results of our paper in the context of Mozambique to accurately highlight limitations.

Data Availability

The scripts and data used to set up the experiments in this study are available from Zenodo at <https://zenodo.org/records/20574212>.

Code availability

The scripts and data used to set up the experiments in this study are available from Zenodo at <https://doi.org/10.5281/zenodo.20574212>.

References

1. Intergovernmental Panel on Climate Change (IPCC). Weather and Climate Extreme Events in a Changing Climate. *Climate Change 2021 – The Physical Science Basis*. (2023). 10.1017/9781009157896.013
2. Intergovernmental Panel on Climate Change (IPCC). *Climate Change 2001: Impacts, Adaptation, and Vulnerability. Working Group II Contribution to the Third Assessment Report of the Intergovernmental Panel on Climate Change* (2001). https://www.ipcc.ch/site/assets/uploads/2018/03/WGII_TAR_full_report-2.pdf
3. Grant, S., Tamason, C. C., Jensen, P. K. M. & Climatization A critical perspective of framing disasters as climate change events. *Clim. Risk Manag.* **10**, 27–34 (2015).
4. Bahinipati, C. S. & Venkatachalam, L. Role of climate risks and socio-economic factors in influencing the impact of climatic extremes: a normalisation study in the context of Odisha, India. *Reg. Environ. Change.* **16**, 177–188 (2014).
5. Bouwer, L. M. Have Disaster Losses Increased Due to Anthropogenic Climate Change? *Bull. Am. Meteorol. Soc.* **92**, 39–46 (2011).
6. Pielke, R. A. Future Economic Damage from Tropical Cyclones: Sensitivities to Societal and Climate Changes. *Philos. Trans. Royal Soc.* **365**, 2717–2729 (2007).
7. Balch, J. K. et al. Social-Environmental Extremes: Rethinking Extraordinary Events as Outcomes of Interacting Biophysical and Social Systems. *Earths Future.* **8**, e2019EF001319 (2020).
8. Raymond, C. et al. Understanding and managing connected extreme events. *Nat. Clim. Chang.* **10**, 611–621 (2020).
9. Chen, A. et al. Impact of tropical cyclones and socioeconomic exposure on flood risk distribution in the Mekong Basin. *Commun. Earth Environ.* **5**, 1–12 (2024).
10. Stolte, T. R. et al. VulneraCity–drivers and dynamics of urban vulnerability based on a global systematic literature review. *Int. J. Disaster Risk Reduct.* **108**, 104535 (2024).
11. Meijer, L. G., Reimann, L. & Aerts, J. C. J. H. Comparing spatially explicit approaches to assess social vulnerability dynamics to flooding. *Int. J. Disaster Risk Reduct.* **96**, 103883 (2023).
12. Modaresi Rad, A. et al. Human and infrastructure exposure to large wildfires in the United States. *Nat. Sustain.* **6**, 1343–1351 (2023).
13. Intergovernmental Panel on Climate Change (IPCC). *Climate Change 2022 – Impacts, Adaptation and Vulnerability. Climate Change 2022 – Impacts, Adaptation and Vulnerability* (Cambridge University Press, 2023). 10.1017/9781009325844

14. Paprotny, D. et al. Attribution of flood impacts shows strong benefits of adaptation in Europe since 1950. *Sci. Adv.* **11**, 7068 (2025).
15. Noy, I., Stone, D. & Uher, T. Extreme events impact attribution: A state of the art. *Cell. Rep. Sustain.* **1**, 100101 (2024).
16. Mengel, M., Treu, S., Lange, S. & Frieler, K. ATTRICI v1.1 - Counterfactual climate for impact attribution. *Geosci. Model. Dev.* **14**, 5269–5284 (2021).
17. Sebastian, A., Gori, A., Blessing, R. B., Van Der Wiel, K. & Bass, B. Disentangling the impacts of human and environmental change on catchment response during Hurricane Harvey. *Environ. Res. Lett.* **14**, 124023 (2019).
18. Zhang, W., Villarini, G., Vecchi, G. A. & Smith, J. A. Urbanization exacerbated the rainfall and flooding caused by hurricane Harvey in Houston. *Nature* **563**, 384–388 (2018).
19. Deng, Z., Villarini, G. & Wang, Z. Climate change dominates over urbanization in tropical cyclone rainfall patterns. *Commun. Earth Environ.* **6**, 1–9 (2025).
20. Smiley, K. T. et al. Social inequalities in climate change-attributed impacts of Hurricane Harvey. *Nat. Commun.* **13**, 3418 (2022).
21. Green, J. et al. A comprehensive review of compound flooding literature with a focus on coastal and estuarine regions. *Hazards Earth Syst. Sci.* **25**, 747–816 (2025).
22. Chakraborty, J., Grineski, S. E. & Collins, T. W. Hurricane Harvey and people with disabilities: Disproportionate exposure to flooding in Houston, Texas. *Soc. Sci. Med.* **226**, 176–181 (2019).
23. Parsons, E. S., Jowell, A., Veidis, E., Barry, M. & Israni, S. T. Climate change and inequality. *Pediatr. Res.* **98**, 1238–1245 (2024).
24. Putsoane, T., Bhanye, J. I. & Matamanda, A. Extreme weather events and health inequalities: Exploring vulnerability and resilience in marginalized communities. *Developments Environ. Sci.* **15**, 225–248 (2024).
25. Harrington, L. J. et al. Poorest countries experience earlier anthropogenic emergence of daily temperature extremes. *Environ. Res. Lett.* **11**, 055007 (2016).
26. Rogers, J. S., Maneta, M. M., Sain, S. R., Madaus, L. E. & Hacker, J. P. The role of climate and population change in global flood exposure and vulnerability. *Nat. Commun.* **16**, 1287 (2025).
27. Hallegatte, S. et al. *Flood Risks, Climate Change Impacts and Adaptation Benefits in Mumbai: An Initial Assessment of Socio-Economic Consequences of Present and Climate Change Induced Flood Risks and of Possible Adaptation Options*. vol. 27 (2010).
https://www.oecd.org/content/dam/oecd/en/publications/reports/2010/11/flood-risks-climate-change-impacts-and-adaptation-benefits-in-mumbai_g17a1f04/5km4hv6wb434-en.pdf
28. McDermott, T. K. J. Global exposure to flood risk and poverty. *Nat. Commun.* **13**, 3529 (2022).
29. Strauss, B. H. et al. Economic damages from Hurricane Sandy attributable to sea level rise caused by anthropogenic climate change. *Nat. Commun.* **12**, 2720 (2021).
30. Data Africa. *Sofala*. (2025). <https://dataafrica.io/profile/sofala-moz>

31. World Meteorological Organisation (WMO). *Tropical Cyclone Idai Hits Mozambique*. (2019).
<https://wmo.int/media/news/tropical-cyclone-idai-hits-mozambique>
32. Probst, P. & Annunziato, A. *Tropical Cyclone Idai: Analysis of the Wind, Rainfall and Storm Surge Impact*. European Commission - Joint Research Centre (2019).
<https://reliefweb.int/report/mozambique/tropical-cyclone-idai-analysis-wind-rainfall-and-storm-surge-impact-9-april-2019>
33. Deprez, S. & Labattut, E. *Lessons Learnt from CARE's Shelter Responses to Cyclone Idai in Malawi, Mozambique and Zimbabwe - Final Report (September)*. reliefweb (2020).
<https://reliefweb.int/report/mozambique/lessons-learnt-care-s-shelter-responses-cyclone-idai-malawi-mozambique-and> (2020).
34. United Nations Office for the Coordination of Humanitarian Affairs (OCHA). Mozambique: Two Cyclones: Idai and Kenneth. (2019).
<https://www.unocha.org/publications/report/mozambique/mozambique-two-cyclones-idai-and-kenneth-22-may-2019>
35. World Population Prospects. <https://population.un.org/wpp/>
36. Mester, B. et al. Human displacements from Tropical Cyclone Idai attributable to climate change. *Hazards Earth Syst. Sci.* **23**, 3467–3485 (2023).
37. Vertegaal, D. M. et al. Climate and impact attribution of compound flooding induced by tropical cyclone Idai in Mozambique. *Nat. Hazards Earth Syst. Sci.* **26**, 1417–1433 (2026).
38. Pesaresi, M. et al. Advances on the global human settlement layer by joint assessment of earth observation and population survey data. *Int. J. Digit. Earth.* **17**, 2390454 (2024).
39. Schiavina, M. & GHS-POP R, F. S. C. A. M. K. A - GHS population grid multitemporal (1975–2030). Preprint at <https://doi.org/> (2023). 10.2905/2FF68A52-5B5B-4A22-8F40-C41DA8332CFE (2023).
40. Intergovernmental Panel on Climate Change (IPCC). Key Risks across Sectors and Regions. Climate Change 2022 – Impacts, Adaptation and Vulnerability 2411–2538. (2023).
10.1017/9781009325844.025
41. van Ormondt, M. et al. SFINCS: Super-Fast INundation of CoastS Model Version 2.2.0 Col d'Eze Release. 01. Zenodo <https://zenodo.org/records/13691724> (2025) (2025) (2025).
10.5281/ZENODO.13691724
42. Kernkamp, H. W. J., Van Dam, A. & Stelling, G. S. De Goede, E. D. Efficient scheme for the shallow water equations on unstructured grids with application to the Continental Shelf. *Ocean. Dyn.* **61**, 1175–1188 (2011).
43. Roelvink, D., van Ormondt, M., Reynolds, J. & van der Lugt, M. SnapWave: fast, implicit wave transformation from offshore to nearshore. *Geosci. Model. Dev.* **18**, 9469–9495 (2025).
44. van Verseveld, W. et al. Deltares/Wflow.jl. (2025).
<https://github.com/Deltares/Wflow.jl/releases/tag/v0.8.1>
45. Pekel, J. F., Cottam, A., Gorelick, N. & Belward, A. S. High-resolution mapping of global surface water and its long-term changes. *Nature* **540**, 418–422 (2016).

46. Rentschler, J., Salhab, M. & Jafino, B. A. Flood exposure and poverty in 188 countries. *Nat. Commun.* **13**, 3527 (2022).
47. Hersbach, H. et al. The ERA5 global reanalysis. *Q. J. R. Meteorol. Soc.* **146**, 1999–2049 (2020).
48. Gahtan, J. et al. International Best Track Archive for Climate Stewardship (IBTrACS) Project, Version 4r01, ALL. (2024). 10.25921/82ty-9e16
49. Knapp, K. R., Kruk, M. C., Levinson, D. H., Diamond, H. J. & Neumann, C. J. The International Best Track Archive for Climate Stewardship (IBTrACS): Unifying Tropical Cyclone Data. *Bull. Am. Meteorol. Soc.* **91**, 363–376 (2010).
50. Knutson, T. et al. Tropical Cyclones and Climate Change Assessment: Part II: Projected Response to Anthropogenic Warming. *Bull. Am. Meteorol. Soc.* **101**, E303–E322 (2020).
51. Rufat, S., Tate, E., Burton, C. G. & Maroof, A. S. Social vulnerability to floods: Review of case studies and implications for measurement. *Int. J. Disaster Risk Reduct.* **14**, 470–486 (2015).
52. Munyai, R. B. et al. Vulnerability and Adaptation to Flood Hazards in Rural Settlements of Limpopo Province, South Africa. *Water (Basel)*. **13**, 3490 (2021).
53. Guo, Y. et al. Cyclone exposure and mortality risk of children under 5 years old: An observational study in 34 low- and middle-income countries. *PLoS Med.* **22**, e1004735 (2025).
54. Mangara, F., Dorasamy, N. & Muzangaza, R. W. Embracing Resilience: Ageing, Disability, and Disasters in Zimbabwe—A Case of Cyclone Idai. *Clim. Resil. Sustain.* **4**, e70020 (2025).
55. Kuhlicke, C. et al. Contextualizing social vulnerability: findings from case studies across Europe. *Nat. Hazard.* **58**, 789–810 (2011).
56. Del Prete, C., Valente, M., Mitiku Saji, A., Khorram-Manesh, A. & Ragazzoni, L. Understanding vulnerability to flood-induced disasters: a comprehensive scoping review on at-risk individuals and evacuation challenges. *BMC Health Serv. Res.* **26**, 171 (2026).
57. Ton, M. J. et al. Spatial 30 arc-second allocation of a global synthetic population using high resolution socio-economic data. *Comput Environ. Urban Syst* (under review).
58. Ton, M. J. et al. GLOPOP-SG. <https://zenodo.org/records/17076088> (2025). 10.5281/ZENODO.17076088
59. Ton, M. J. et al. A global dataset of 7 billion individuals with socio-economic characteristics. *Sci. Data.* **11**, 1–11 (2024).
60. Instituto Nacional de Estatística (INE). Sofala - District statistics. (2025). <https://www.ine.gov.mz/web/guest/d/07-sofala>
61. Sauer, I. J. et al. Climate signals in river flood damages emerge under sound regional disaggregation. *Nat. Commun.* **12**, 2128 (2021).
62. Perkins-Kirkpatrick, S. E. et al. Frontiers in attributing climate extremes and associated impacts. *Frontiers Climate* **6**, (2024).
63. Lincke, D., Hinkel, J., Mengel, M. & Nicholls, R. J. Understanding the Drivers of Coastal Flood Exposure and Risk From 1860 to 2100. *Earths Future* **10**, e2021EF002584 (2022).

64. Mixed Migration Centre (MMC). *Climate and Mobility Case Study January 2023: Beira, Mozambique: Praia Nova*. (2023). <https://reliefweb.int/report/mozambique/climate-and-mobility-case-study-january-2023-beira-mozambique-praia-nova>
65. Pinto, I. et al. La Niña, Climate Change, High Exposure and Vulnerability Combined Led to Devastating Floods in Parts of Southern Africa. *WWA Sci.* 10.25560/127388 (2026).
66. Williamson, C., McCordic, C. & Doberstein, B. The compounding impacts of Cyclone Idai and their implications for urban inequality. *Int. J. Disaster Risk Reduct.* **86**, 103526 (2023).
67. Moreira, L. L., De Brito, M. M. & Kobiyama, M. Review article: A systematic review and future prospects of flood vulnerability indices. *Nat. Hazards Earth Syst. Sci.* **21**, 1513–1530 (2021).
68. Rufat, S. Spectroscopy of Urban Vulnerability. *Ann. Assoc. Am. Geogr.* **103**, 505–525 (2013).
69. Mugabe, V. A., Gudo, E. S., Inlamea, O. F., Kitron, U. & Ribeiro, G. S. Natural disasters, population displacement and health emergencies: multiple public health threats in Mozambique. *BMJ Glob Health.* **6**, e006778 (2021).
70. Webb, P. E., Vertegaal, D. M., Vogel, M., Jack, C. & Muis, S. Impact attribution of compound flooding from Tropical Cyclone Idai: Assessing the influence of land cover change and underlying socio-economic drivers using a mixed-methods approach. *Natural Hazards Earth Syst. Sciences* (under review).
71. Sauer, I. J. et al. Limited progress in global reduction of vulnerability to flood impacts over the past two decades. *Commun. Earth Environ.* **5**, 239 (2024).

Figures

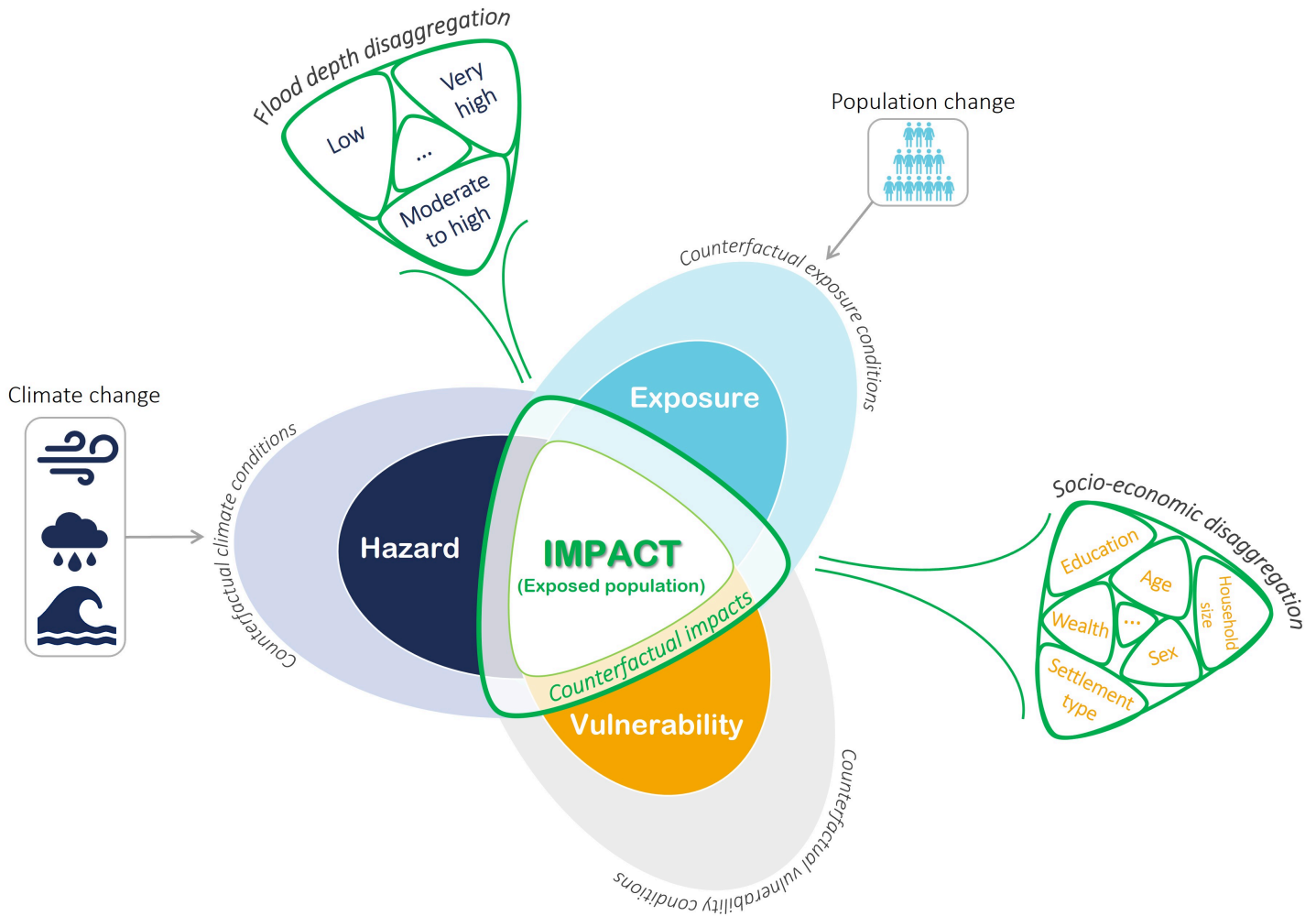


Figure 1

Conceptual overview of attributing the impact of compound flooding due to changes in climate and exposure conditions that influence different parts of the risk framework. TC maximum wind speeds, rain, and SLR can alter the climate conditions, and population change can alter exposure conditions, all potentially exacerbating flood impact. The exposed population to flooding is used as impact metric. The impacts are disaggregated per flood depth category and per socio-economic characteristics of the population. Adapted from Figure 16.1 in IPCC AR6 report⁴⁰.

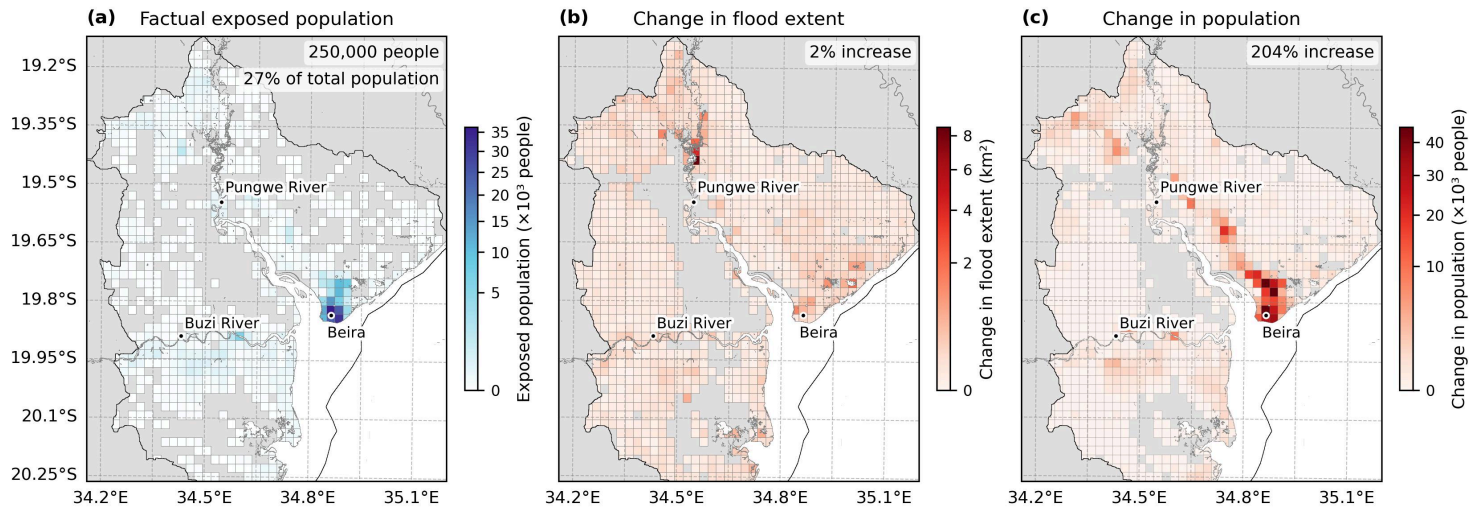


Figure 2

The factual exposed population and changes in climate change and population change since 1975.

Panel a shows the population exposed by compound flooding from TC Idai in the factual scenario with a total of 250,000 people, which is 27 % of the total population in the case study area. Panel b shows the attributable flood extent to climate change since 1975, accounting for a 2 % increase. Panel c shows the change in population within the case study area since 1975, accounting for a 204 % increase. The population is aggregated to grid cells of 2.5 km for visualisation. The flood model domain is outlined in black. The city Beira and major rivers are annotated in every panel.

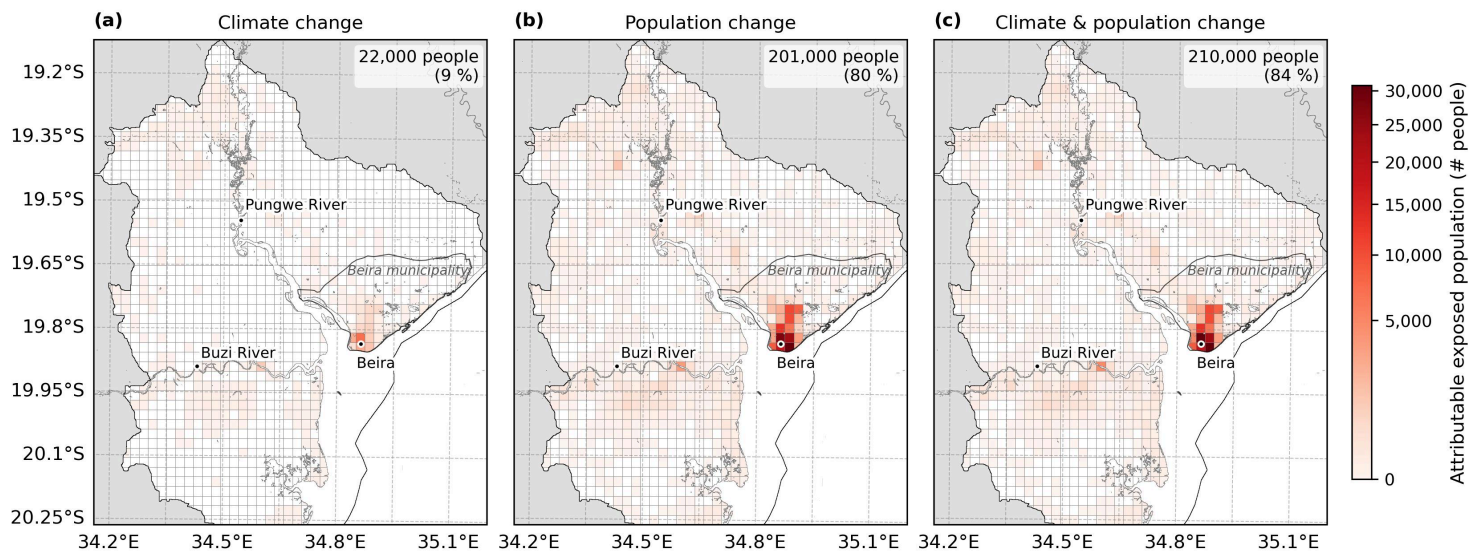


Figure 3

The attributable fraction of the population exposed to flooding from TC Idai. Every panel shows the difference between the factual scenario exposed population in the compared to counterfactual scenario, aggregated to grid cells of 2.5 km for visualisation. Panel a shows the effect of climate change, panel b the effect of population change, and panel c their combined effect. The total difference aggregated over

the case study area is presented in the top right corner, together with the total attributable fraction (according to Eq. 1). The flood model domain is outlined in black, and the Beira municipality in grey. The city Beira and major rivers are annotated in every panel. Small negative values occur but are omitted for visualisation purposes.

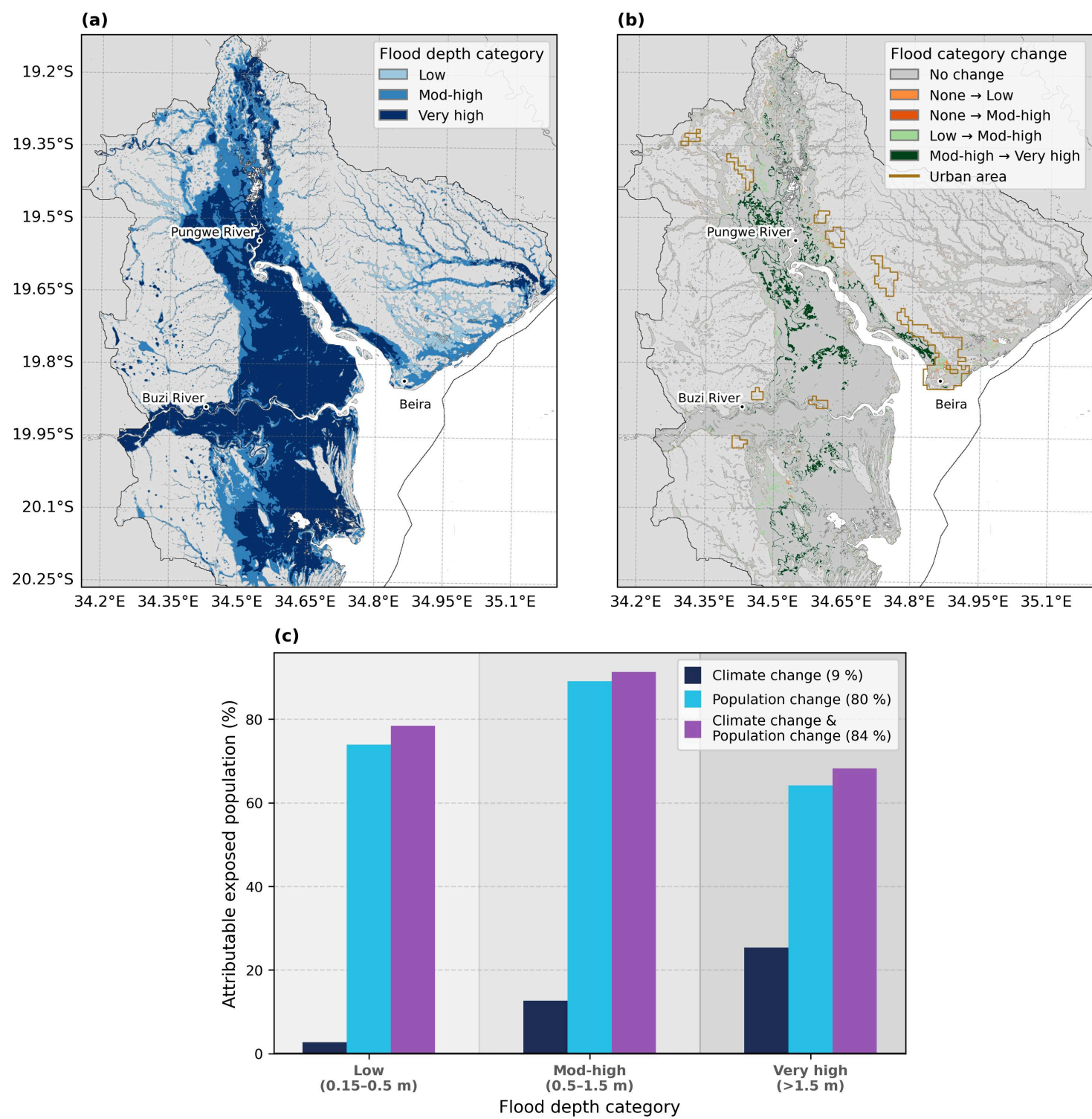


Figure 4

The fraction of the exposed population attributable to climate and population change per flood depth category. The attributable fraction is considered relative to the total exposed population per flood depth category (according to Eq. 1). The dark blue bars show the fraction attributable to climate change. The light blue bars show the fraction attributable to population change. The purple bars show the fraction attributable to climate and population change combined. For panel a and b, the flood model domain is outlined in black, and Beira and the major rivers are annotated. The urban areas based on the dataset from Ton et al.^{57,58} are outlined in yellow in panel b.

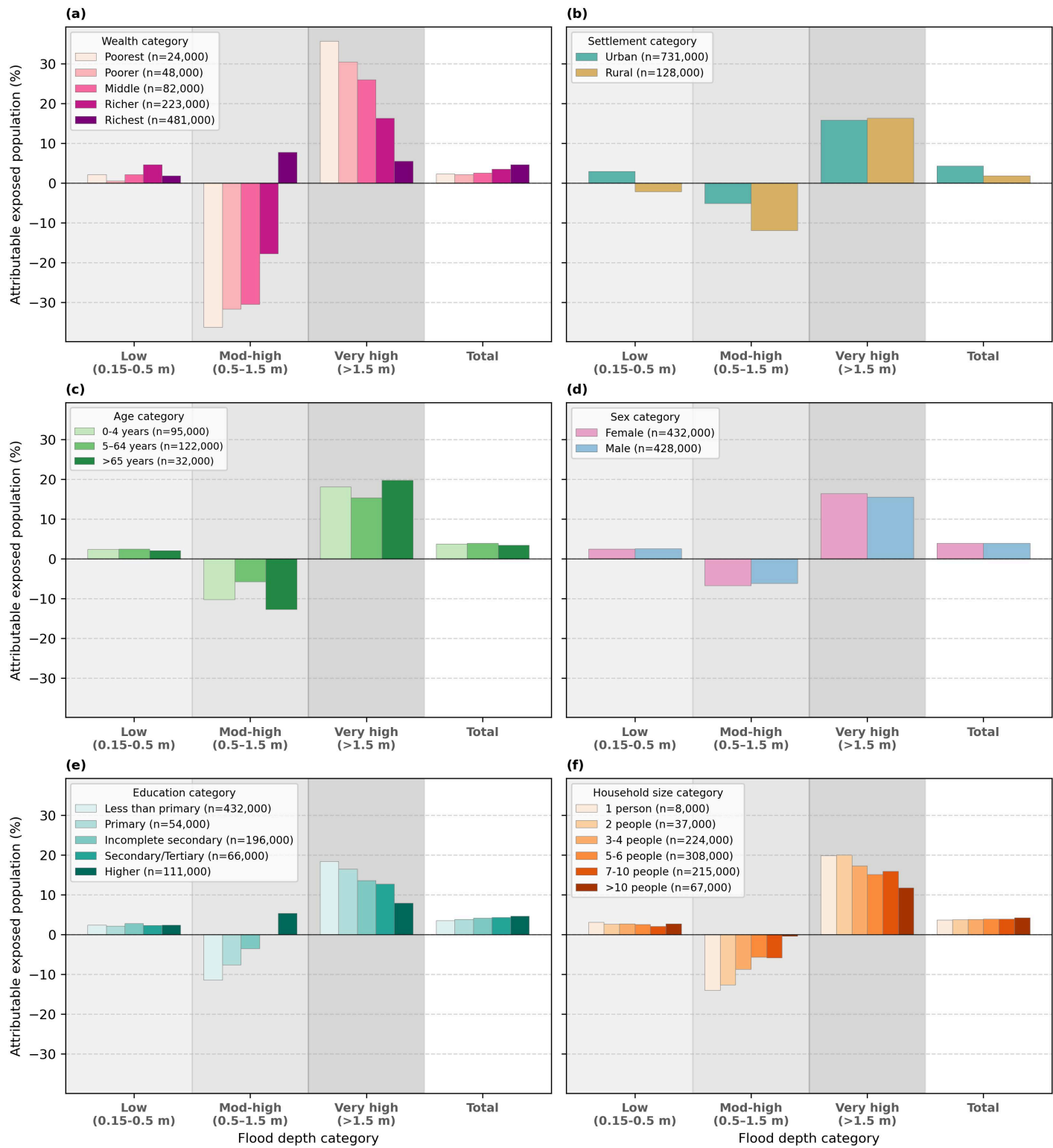


Figure 5

The fraction of the exposed population attributable to climate change across flood depth categories and socio-economic characteristics of the population. The “Total” flood depth category aggregates the attributable fraction over all flood depths and is therefore a binary impact classification. Panel a, b, c, d, e, and f show the attributable fraction per flood depth category and regardless of flood depth (Total) for wealth, settlement type, age, sex, education, and household size, respectively. The total number of people per socio-economic category is annotated in the legend. Low, moderate-to-high (abbreviated to “Mod-high”) and very high flood depths consider 0.15 m – 0.5 m, 0.5 m – 1.5 m, and > 1.5 m, respectively.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [VertegaaletalSupplementarymaterial260520261.docx](#)