



# Climate and impact attribution of compound flooding induced by tropical cyclone Idai in Mozambique

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Abstract. In this study, we investigate the effect of climate change on tropical cyclone (TC) induced compound flooding and impacts for TC Idai, making landfall in Mozambique in 2019. TCs are one of the most damaging extreme events and are challenging to attribute using conventional, probabilistic methods. We develop a storyline attribution framework including a state-of-the-art modelling chain that combines hydrological, coastal, flood and impact models to simulate the changes in flooding and its impact under factual and counterfactual scenarios, with the climate trend removed. For the case of TC Idai, we find that sea level rise and change in wind-driven storm surge lead to the largest increase in flood damage (27 % compared to the counterfactual), while causing a less than 1 % increase in flood volume and flood extent. Climate trends in rainfall lead to the largest increase in flood volume and flood extent (9 % and 2 %, respectively, compared to the counterfactual) but account for a smaller increase in flood damage (4 %). Changes in all drivers combined lead to the same increase in flood volume and flood extent as the rain-only scenario (9 % and 2 %, respectively) but the largest increase in flood damage (31 %). A nonlinear relationship between flood hazard and flood damage results in a stronger climate footprint on TC impacts than hazards. Assessing the combination of all climate change-affected flood drivers is crucial for obtaining a comprehensive view on the effect of climate change. The attribution framework presented in this paper is applicable for TC-prone regions across the globe and can be applied in data-poor, yet often highly impacted and vulnerable areas which are currently underrepresented in attribution studies.

# Short summary (500 characters incl. spaces):

This study highlights the need to disentangle climate change effects on flood drivers using storyline attribution. Whether the information is presented as change in one or multiple drivers, or as change in hazard or impact, determines the attribution statement. For the compound flooding from tropical cyclone Idai, that hit Mozambique in 2019, we attribute up to 9 % of the flood hazard and 31 % of the damage to climate change. The attribution framework can be applied to other events worldwide.

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# 1 Introduction

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Compound flooding from tropical cyclones (TCs) is one of the most damaging climate extreme events and is exacerbated by climate change (Frame et al., 2020; Smith and Katz, 2013). This raises the question to what extent climate change is already worsening the occurrence and severity of TCs. This question is being addressed by climate attribution, which is a rapidly emerging academic field, aiming to assess the contribution of climate change to extreme events (Hegerl et al., 2010; Intergovernmental Panel on Climate Change (IPCC), 2014).

There are various attribution methods; ranging from probabilistic using climate model ensembles to (semi-)conditional analogues and storylines (Faranda et al., 2022; van Garderen et al., 2021; van Oldenborgh et al., 2021; Stott et al., 2004). Most climate attribution assessments focussing on flood events use a meteorological driver as a proxy to represent the flood hazard, such as 3-day annual maximum precipitation (Davenport et al., 2021; Otto et al., 2022; Wang et al., 2023). However, flooding involves many non-linear processes that depend not only on the amount and intensity of local rainfall. The rainfall—runoff response is controlled by catchment size, antecedent conditions, land cover, elevation, and other factors (Jahanshahi and Booij, 2023; Massari et al., 2023). Without the modelling of the flood event and associated drivers, it remains uncertain what aspect of the flood event is attributable to climate change (Scussolini et al., 2024). Moreover, attribution studies that do propagate the effect of climate change to flood hazard often model a single flood driver (Mester et al., 2023; Strauss et al., 2021), ignoring the interaction of multiple flood drivers, such as pluvial, fluvial or coastal flooding, that often co-occur during TC events (Ward et al., 2018).

TCs are particularly challenging to attribute using conventional, probabilistic attribution methods (Philp et al., 2022). The reason is that probabilistic attribution relies on accurate model representation and good quality observations, which both have been shown to be challenging for TCs due to their relatively small spatial scale compared to climate model resolution, limited understanding of the underlying physics, their short observational records, and large internal variability (Camargo et al., 2023; Knutson et al., 2019; Philip et al., 2020)

Instead of attributing all causal factors simultaneously, storyline attribution examines the causality chain through conditional explanations (e.g. conditioning on atmospheric dynamics) (Shepherd, 2016; Sillmann et al., 2021). Studying the plausibility rather than probability allows for assessing contributions of separate drivers affected by climate change, which is necessary for describing complex extremes such as TCs (Lloyd and Shepherd, 2021; Perkins-Kirkpatrick et al., 2024). A storyline approach is applicable for compound flooding from TCs and has been applied for event attribution (Mester et al., 2023).

60 By modelling a comprehensive causality chain between hazards and impacts, storyline attribution also enables impact attribution, which builds on climate attribution. Impact attribution propagates the effect of climate change from hazard to

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impact and includes elements of exposure and vulnerability contributing to societal impact (IPCC, 2023a; Mengel et al., 2021; Noy et al., 2024). By integrating the role of exposure and vulnerability, impact attribution helps improving climate impact assessments (IPCC, 2023a). It can be used to inform policies and actions and can help improve the description of the links between climate phenomena and impacts (Hope et al., 2022).

Highly vulnerable and low-income regions, such as those in East Africa, remain underrepresented in attribution studies (Callaghan et al., 2021; Coumou et al., 2024; Perkins-Kirkpatrick et al., 2024). Most TC attribution studies focus on data-rich regions, like the United States (Bourdin et al., 2025; Grimley et al., 2024; Smiley et al., 2022; Strauss et al., 2021). This attribution gap is at least partly related to the lack of observational data. However, recent advances in global flood modelling (Ward et al., 2015; Wing et al., 2024) have created new information sources, including globally applicable methods for tropical-cyclone induced flooding (Benito et al., 2025; Eilander et al., 2023a). These developments pave the way for addressing the attribution gap and building a globally applicable method for storyline attribution of TC-induced flooding.

The goal of this paper is to demonstrate the applicability of an attribution framework utilizing global data and methods by attributing the effects of climate change on flood hazard and impact from TC Idai. TC Idai was one of the most devastating cyclones to ever hit the southern hemisphere (Warren, 2019). On 14 March 2019, it made landfall close to Beira City in Mozambique. A seven-day accumulated rainfall of more than 600 mm, strong winds above 150 km/h and storm surge heights estimated at 2.5 to 4.4 m impacted Mozambique, Malawi and Zimbabwe (Probst and Annunziato, 2019; WMO, 2019). In Mozambique alone, it is estimated that Idai caused over 3 billion USD in economic costs, destroyed over 200,000 homes, and caused 600 fatalities (Nhundu et al., 2021; OCHA, 2019). The storm ultimately affected approximately 1.85 million people across Mozambique. Also in the future, Mozambique is expected to be the highest impacted country by TCs in East Africa (Benito et al., 2024).

We use a storyline attribution framework with a state-of-the-art modelling chain that dynamically simulates all TC flood drivers and damages in factual and counterfactual scenarios, where climate change trends are removed. The differences between the factual and counterfactual scenarios for flood hazard and impact are compared to construct climate and impact attribution assessments. Finally, we discuss the results and recommend further improvements for our attribution framework and directions for climate and impact attribution assessment of compound flooding from TCs.

# 90 2 Methodology

The attribution framework (Fig. 1) for TC Idai (9 to 25 March 2019) consists of multiple physics-based models for the different flood drivers (Sect. 2.1) and a flood impact model (Sect. 2.2). These models are used to simulate a factual scenario (Sect. 2.3.1) and multiple counterfactual scenarios with the climate change trend removed from rainfall, wind and sea level (Sect. 2.3.2). The factual and counterfactual scenarios are compared in terms of change in flood hazard (volume and extent) and flood impact





(direct damage) to determine the climate- and impact attribution (Sect. 2.3.3). Our entire workflow is built on open-source models and is accessible on GitHub (Vertegaal et al., 2025).

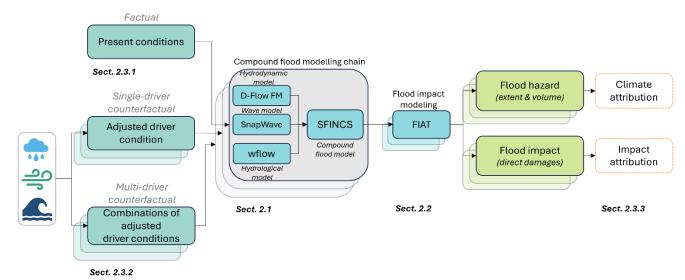


Figure 1: Attribution framework consisting of steps to assess climate- and impact attribution for compound flooding from TCs. The compound flood modelling (Sect. 2.1) and flood impact modelling (Sect. 2.2) is applied to a factual (Sect. 2.3.1) and multiple counterfactual scenarios (Sect. 2.3.2), and is used to simulate flood hazard (volume and extent) and flood impact (direct damages). The input data for the different counterfactuals is based on changes in wind, rainfall and sea level rise. Stacked boxes show multiple (combined) adjusted driver conditions, model simulations or analyses. Climate attribution refers to the changes due to climate change on the hazard, whereas impact attribution propagates the effect to impact (Sect. 2.3.3).

#### 2.1 Compound flood modelling

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The modelling chain we develop for simulating the TC-induced compound flooding (fluvial, pluvial and coastal) is based on the Super-Fast INundation of CoastS v2.2.0 (SFINCS) model (van Ormondt et al., 2025a), building on the globally-applicable method presented in Eilander et al. (2023a). Discharge boundary conditions are modelled with the hydrological model wflow v0.8.1 (van Verseveld et al., 2025). Coastal water level boundary conditions are modelled with hydrodynamic model D-Flow FM v2025.01 from the Delft3D Flexible Mesh Suite (Kernkamp et al., 2011) to compute tide and storm surge. Nearshore wave setup is modelled using the coupled wave model SnapWave (Roelvink et al., 2025), that is integrated into SFINCS (Leijnse et al., 2025). The forcing for the factual and counterfactual scenarios is described in Sect. 2.3. Details on model parameters can be found in the GitHub repository (Vertegaal et al., 2025). To setup the models and process the in- and output, we make use of the python package Hydro Model Tools (HydroMT) with the model specific plugins (Deltares, 2025; Eilander et al., 2023b, 2024, 2025), except for the D-Flow FM model where we make use of dfm tools v0.35 (Veenstra, 2025).

#### 115 **2.1.1** Compound flooding

Compound flooding is simulated using the SFINCS model, a reduced-complexity and computationally efficient model (Leijnse et al., 2021). SFINCS has been successfully used to simulate TC-induced flooding in various studies (Benito et al., 2024, 2025;



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Eilander et al., 2023a; Goulart et al., 2024; Grimley et al., 2024; Leijnse et al., 2025; Nederhoff et al., 2024). In this study, SFINCS is forced with river discharges (Sect. 2.1.2), coastal water levels (Sect. 2.1.3) and local rainfall (Sect. 2.3.1. & 2.3.2). The spatial resolution of the model is 100 m and the domain covers 8260 km² (pink domain in Fig. 2). To reduce computational costs, we make use of the subgrid functionality that applies corrections of the flow momentum and continuity equation for bed level and friction variability within a cell and downscale the results to the higher resolution digital elevation model of 25 m (van Ormondt et al., 2025b). For topobathy, we merge the global bathymetry dataset GEBCO (GEBCO Bathymetric Compilation Group 2024, 2024) with the FABDEM digital elevation model (Hawker et al., 2022). Land Manning roughness is based on the land use data from Buchhorn et al. (2020) and infiltration data from Jaafar and Ahmad (2019). Flooded areas are identified by removing permanent water areas, using the Global Surface Water dataset (Pekel et al., 2016). A cell is considered as flooded if the water depth exceeds 0.05 meter.

#### 2.1.2 River discharge

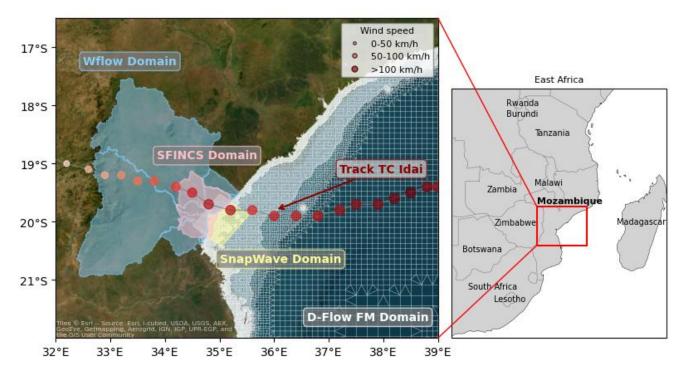
River discharge is simulated using the wflow model (van Verseveld et al., 2024), which is a distributed hydrological model. To account for the antecedent conditions, the wflow simulations consist of a warm-up run covering 365 days prior to the event, which provides the initial state for the event run. The wflow model has a spatial resolution of 0.0083° (~1 km). The model domain covers around 68,000 km², entailing the catchments from the Pungwe and Buzi rivers (blue domain in Fig. 2). MERIT Hydro is used as hydrography data (Yamazaki et al., 2019), together with river geometries from Lin et al. (2019), and lakes and reservoirs from Lehner et al. (2022) and Linke et al. (2019). We use the same land cover dataset as for the SFINCS modelling (Buchhorn et al., 2020). Hourly output is generated at the river inflow points of the SFINCS model domain (Fig. S1) from which we remove the bankfull discharge (estimated as the 2-year return period; Wilkerson, 2008) to account for missing river bathymetry (Sect. S1.2).

# 2.1.3 Coastal water levels

Coastal water levels are composed of tides, storm surge, and wave setup (IPCC, 2023b). The tide and storm surge are simulated using a regional hydrodynamic D-Flow FM model. The spatially-varying grid has a resolution of ~2 km in the deep ocean and 450 m at the coast. The finest resolution aligns with that of the GEBCO bathymetry dataset (GEBCO Bathymetric Compilation Group 2024, 2024). The model stretches along the whole coast of Mozambique (white domain in Fig. 2), covering 1,117,000 km². We combine the tide and surge with dynamically modelled wave setup, calculated from the SnapWave simulation. The SnapWave model has a spatially-varying grid with a resolution of 400 m off-shore to 50 m at the coast, covering an area of 5400 km² (yellow domain in Fig. 2). The D-Flow FM output is generated around the 5-meter depth contour within the SFINCS domain at a 10-minute temporal resolution (Fig. S1). The SnapWave output is also generated at a 10-minutes temporal resolution but for coastal transects. The wave setup is added to the D-Flow FM output at the same 5-meter depth contour (Sect. S1.4).







150 Figure 2: Overview of the different model domains to simulate the compound flooding (SFINCS domain in pink), river discharge (wflow domain in blue) and coastal water levels (a part of the D-Flow FM domain in white; SnapWave domain in yellow). We also show the track of TC Idai from IBTrACS, where larger and more red coloured markers indicated higher wind speed.

#### 2.2 Impact modelling

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The fast impact assessment tool Delft-FIAT v0.3.2 (Wagenaar et al., 2017) is used to calculate direct flood damage by overlaying maximum flood depths with building footprints. The damage is calculated using the continental depth-damage curves for flooding and maximum potential damage per building type for Africa (Moel et al., 2017), similar to Eilander et al. (2023b) and Goulart et al. (2025). The currency of the maximum potential damage is in 2010 Euros, which is converted to 2019 US Dollars using a 2010 Euro-to-USD exchange rate of 1.327 and adjusted for inflation using a 2010-to-2019 USD rate of 1.172 (Archived Consumer Price Index Supplemental Files, 2025).

We use building footprints and type from OpenStreetMap (OSM; OpenStreetMap contributors, 2025) since it provides a recent and good coverage of the region, including rural areas and so-called informal settlements (Herfort et al., 2023; Wagenaar et al., 2018a; Zhou et al., 2022). The output is generated as total and relative damage (damaged fraction of the total asset value) per building, which is aggregated to cells of 0.025° and to the total compound flood domain.



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## 2.3 Scenarios for attribution

#### 2.3.1 Factual scenario

For the factual scenario, we make use of various datasets as meteorological and hydrodynamic forcing. The main meteorological forcing used is the ERA5 reanalysis dataset (Hersbach et al., 2020), available at hourly and daily temporal resolution and  $0.25^{\circ}$  (~30 km) spatial resolution. ERA5 provides one of the best source of globally complete and consistent historical climate data. The compound flood model SFINCS is forced with ERA5 hourly rainfall. The hydrological model wflow is forced with ERA5 daily (warm-up run) and hourly (event run) rainfall and temperature data. The wave model SnapWave is forced with ERA5 hourly wave conditions as the significant wave height. Since ERA5 underestimates the intensity of TCs (Dullaart et al., 2020), we use best track data (IBTrACS; Gahtan et al., 2024; Knapp et al., 2010) in combination with the Holland parametric model (Holland, 2008; Holland et al., 2010) to calculate TC wind and pressure forcing for the D-Flow FM and SFINCS models. The TC wind and pressure fields are merged with hourly background wind and pressure data from ERA5 by linearly fading the data at 0.75 fraction of the TC radius. In addition to the meteorological forcing, the regional D-Flow FM model is forced with tidal boundary conditions derived from the Global Tides and Surge Model (GTSM) v4.1 (Wang et al., 2022).

#### 2.3.2 Counterfactual scenarios

For the counterfactual scenario, we adjust the forcing of the factual scenario by removing the long-term climate trends. Climate 180 change is affecting TCs in multiple ways, with varying levels of scientific agreement. We focus on changes in rainfall, maximum wind speed and sea level rise (SLR) since there is a clear scientific consensus about the role of climate change on these drivers (Knutson et al., 2020). For the counterfactual scenarios, we adjust each of these drivers by removing the climate change trend. We assess the effect of changes for the three individual flood drivers as well as their combined effect (Table 1 185 and S2). A complete description of the methodology that describes those changes is provided in Sect. S1.6. In all counterfactual scenarios, we keep the same TC track as the one observed during the factual event. Similar to Goulart et al. (2025), we adopt the Clausius Clapeyron relationship for the change in rainfall due to climate change. As Idai took place in a ~1.1 °C warmer world, this results in a 8 % reduction of rainfall for the counterfactual scenario. Following Mester et al. (2023), we use a 10 % reduction in maximum wind speed for the counterfactual scenario. This value is based on regional trends from observed TCs, 190 and falls within the likely range of 2-11 % by Knutson et al. (2020). We use the dataset by Treu et al. (2024) to estimate the SLR between the time of the event and pre-industrial levels. This results in a SLR of 14 cm for the counterfactual scenario, which is removed from the coastal boundary condition and initial water levels.

For all counterfactual scenarios, we assume that wave setup is the same as for the factual scenario. This simplification is made because our framework does not include a deep-water wave model, which would be required to generate a counterfactual

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scenario. For the case of TC Idai, we consider this a valid assumption given that waves are of limited importance for coastal flooding due to the shallow and gentle sloping coast that stimulates wave dissipation (van Dongeren et al., 2007).

Table 1: Overview of counterfactual runs where the climate change trend is removed for rain, wind and sea level rise. See Table S2 for all combinations of drivers.

Climate driver adjusted	Rainfall change	Wind change	SLR	
Rain	-8 %	-	_	
Wind	_	-10 %	_	
SLR	SLR –		-0.14 m	
Wind & SLR	Wind & SLR –		-0.14 m	
All	All -8 %		-0.14 m	

#### 2.3.3 Climate and impact attribution

The change in flood hazard and impact attributable to climate change is expressed following Eq. (1):

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

Where A is the attributable change in %, F is the selected variable from factual scenario and CF from the counterfactual scenario.

For the climate attribution assessment, the flood volume and flood extent of the factual and counterfactual scenarios are compared, similar to Grimley et al. (2024) and Mester et al. (2023). The flood extent is calculated by summing the cell area of all cells considered as flooded. The flood volume is calculated by multiplying the cell area of every flooded cell with its flood depth, and then summing the volume of all flooded grid cells to obtain the total flood volume. For the impact attribution assessment, the total damage from Delft-FIAT is calculated by summing the flood damage of all flooded buildings.

#### 3 Results

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# 3.1 Description of the factual event

TC Idai caused widespread flooding covering 3600 km<sup>2</sup>, affecting mostly the floodplains of the Pungwe and Buzi rivers, and the city of Beira (Fig. 3, left panel). Most of the flooding is driven by the extensive fluvial flooding from the Buzi and the

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Pungwe rivers, with peak discharges of 27,000 m<sup>3</sup>/s and 5,000 m<sup>3</sup>/s, respectively, compared to 4,000 m<sup>3</sup>/s and 2,000 m<sup>3</sup>/s under normal conditions (Table S1). The extreme discharge in the Buzi river leads to flood depths of > 3.5 m along the river banks. Local rainfall, which amounted to a mean of 420 mm accumulated during the time of the event over the study area, partially flooded the more elevated area northeast of Beira. The flooding in the city of Beira, however, is largely driven by coastal flooding as a result of coastal water levels up to 4.3 m + m.s.l. (near Beira). Despite occurring close to neap tide, it exceeds water levels during normal high tide with about 0.6 meter, and coincides with the peak rainfall (Fig. S13). The wave setup accounted for 10 % of the maximum total water level.

In total, 84,000 buildings are estimated to be flooded with damages adding up to 349 million USD. The flooding from TC Idai particularly impacts the city of Beira (Fig. 3, right panel). About 79% of the total damage is situated in the Beira region. However, when considering relative damages (damaged fraction of the total asset value), the floodplains of the Pungwe and the Buzi, and the most southern estuary, are more severely damaged (Fig. 6).

#### 3.2 Model validation

We compare the factual scenario against available observations and reported values in literature. Validating individual flood drivers is challenging due to lack of observations for rainfall and water levels during the event. For discharge, we can only compare against observations for the period 1954-1984 (The Global Runoff Data Centre, 2025). This comparison shows that the simulated discharge for the two major rivers in the region (the Pungwe and Buzi) captures the seasonal and long-term dynamics reasonable to well (KGE 0.28 and 0.87 for the Pungwe and Buzi rivers, respectively; Fig S5), although extremes are generally overestimated (Fig. S6). The overestimation of extreme discharge may be related to the limited calibration of the wflow model and reported overestimation of ERA5 rainfall for tropical cyclone Idai (Jaffrés and Gray, 2023). For TC Idai, the simulated discharge is in the same order of magnitude as calculated by Eilander et al. (2023a). No tide gauge stations are available but our simulated coastal water levels are consistent with Probst & Annunziato (2019) and Eilander et al. (2023a). However, Eilander et al. (2023a) estimate a wave setup of up to 24 % of the total water level, calculated using a simplified empirical approach that is known to overestimate wave setup (Leijnse et al., 2025), compared to our estimate of 10 % wave setup resulting from dynamic wave modelling.

The maximum flood extent is validated against two satellite products, which show reasonable agreement (hit rate >76 %), but also considerable uncertainty in flood detection (Sect. S1.5). Our maximum flood extent is consistent with Mester et al. (2023) and Eilander et al. (2023a), although compared to the latter our results indicate more extensive coastal flooding in the Beira region. This can be explained by the modelling setup with higher-resolution regional coastal models, which results in higher coastal boundary conditions (Benito et al., 2025).





With regards to the flood damage, the Government of Mozambique (2019) estimated the total housing damages at 410 million USD for the Sofala, Manica, Tete and Zambezia provinces in Mozambique. Our estimated damage of 349 million USD only includes the most heavily impacted Sofala province and is thus in agreement with reported damages.

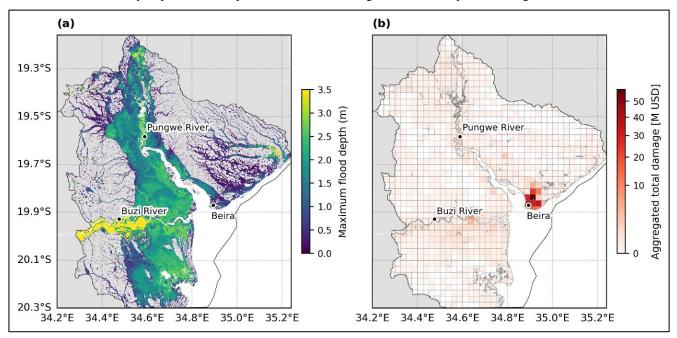


Figure 3: Simulated maximum flood depths in meters (a), and aggregated (0.025° grid cells) total damage in million (M) USD (b) due to flooding for the factual scenario of TC Idai. The compound flood model (SFINCS) domain is shown in black.

## 3.3 Climate and impact attribution

# 3.3.1 Climate attribution

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The increase in flood volume and flood extent that can be attributed to climate change is 9 % and 2 %, respectively, corresponding to an increase of > 500 M m³ and > 85 km² (Table 2). The difference between change in flood volume and flood extent can be related to the region's topography, where higher elevated areas inhibit the extension of the flooded area. The climate change-induced rainfall leads to the largest increase in flooding (Fig. 4), with an increase of 9 % in flood volume and 2 % in flood extent when comparing against the counterfactual. Climate change-induced wind speed and SLR lead to less than 1 % increase in flood volume and flood extent. Still, changes in wind and SLR intensify the coastal flooding, which primarily affects the Beira region covering 270 km². This in contrast to the climate change-induced rainfall, which intensifies river flooding in a widespread area, covering 3420 km². The intensified river flooding affects the floodplains of the Buzi river the most, with an increase in flood depth of > 0.5 m. The intensified coastal flooding also reaches up to > 0.5 m. Our results show that the counterfactual adjustment of individual flood drivers exhibits negligible compounding effects in flood volume and flood extent due to the relatively small effect of climate change-induced wind and SLR.





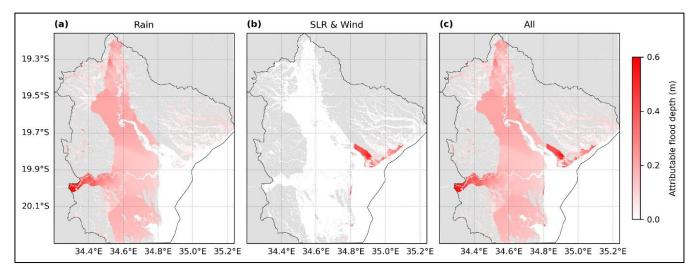


Figure 4: The flood depth attributable to climate change (factual – counterfactual) from different flood drivers; rain (a), wind and SLR (b), and all drivers combined (c). The compound flood model (SFINCS) domain is shown in black.

Table 2: The absolute and relative change in flood volume, flood extent and flood damage for factual (absolute values only) and counterfactual scenarios. The relative change in flooding and impact that is attributable to climate change is calculated by applying Eq. 1.

Scenario	Flood volume		Flood extent		Flood damage	
	Absolute value	Relative	Absolute value	Relative	Absolute value	Relative
	$[M m^3]$	change	[km²]	change	[M USD]	change
Factual	5502	-	3592	-	349	-
Counterfactual						
Rain	5023	9 %	3526	2 %	334	4 %
SLR	5488	< 1 %	3589	< 1 %	313	10 %
Wind	5474	< 1 %	3577	< 1 %	280	20 %
SLR & Wind	5463	< 1 %	3574	< 1 %	256	27 %
All	4984	9 %	3507	2 %	240	31 %

# 3.3.2 Impact attribution

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Comparing the factual and counterfactual scenarios shows that 31 % (109 M USD) of the flood damage can be attributed to climate change. Climate change-induced wind and SLR lead to the largest increase in damage of 27 %, whereas climate change-induced rainfall leads to an increase of 4 % (Table 2). Even though changes in SLR and wind are negligible in terms of changes in flood volume and flood extent, these drivers have a larger impact on flood damage than changes in rainfall (Fig. 5). The relative change in impact is larger than the relative change in flooding, except for the rain-only scenario. Increased wind and



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SLR intensify coastal flooding, which is the main driver of damage in Beira, where total damages are concentrated due to the high density of buildings (Fig. 3, Fig. S14). When adjusting wind and SLR individually, wind emerges as a more significant driver of flood damage than SLR (Table 2). Since wind and SLR impact the same region, their individual impacts on damage are not additive; increases in flood depth translate non-linearly to damage due to the applied damage curves. In this case, there is a limited (< 1 %) compounding effect of attributing all flood drivers combined, as the increased rain-driven flooding (pluvial and fluvial) impacts buildings in different areas than the increased coastal flooding. Changes in all drivers combined leads to the largest changes in flood damage. Our results show that propagating the effects of climate change from hazard to impact influences the attribution assessment. The location of climate change-induced flooding is crucial in determining impacts, highlighting the role of exposure and vulnerability.

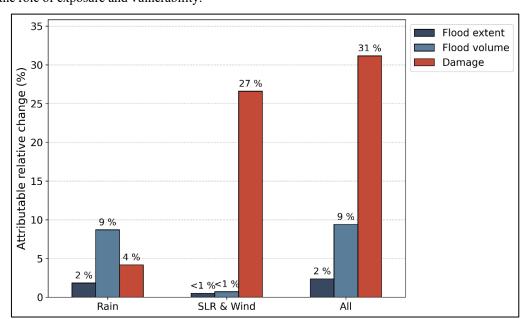


Figure 5: The relative change in flood extent (dark blue), flood volume (light blue), and flood damage (red) due to climate change between the factual and counterfactual scenarios, driven by different flood drivers where "All" includes SLR, wind and rain. The relative change in flooding and impact is calculated by subtracting the counterfactual from the factual value (Eq. 1; Sect. 2.5).

Relative damage, i.e. damaged fraction of the total asset value, provides another perspective on the impacts of climate change. While Beira appears as a hotspot for total damage attributable to climate change (Fig. S14); when considering relative damages, areas across the floodplains become more prominent (Fig. 6). When focusing on relative damage, increased rainfall is the most important driver of additional damage compared to wind and SLR. Only looking at aggregated urban areas that are usually the hotspot of capital, and therefore more likely of total damage, provides a biased view on the impacts of climate change. Within urban areas, the compounding impacts of TC Idai have been found to increase inequality and highlight the need for local studies considering how the impact and response is distributed (Williamson et al., 2023).





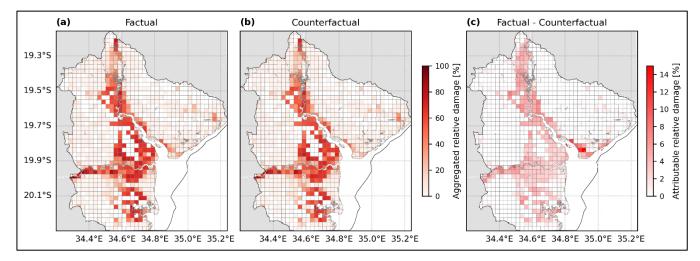


Figure 6: The aggregated (0.025° grid cells) relative damage (damaged fraction of total asset value) for the factual (a) and counterfactual (b) scenarios with all drivers combined, and the absolute difference (factual – counterfactual) attributable to climate change (c). The compound flood model (SFINCS) domain is shown in black.

#### 4 Discussion

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In this paper, we present a storyline attribution framework with a state-of-the-art modelling chain for TC compound flooding. To our knowledge, this is the first framework resolving all TC flood drivers (local rainfall, discharge, tides, storm surge and wave setup) using physics-based models and attributing them to climate change. This framework accurately reproduces compound flooding from TC Idai using global data, which is applied for both climate and impact attribution assessments. In the case of compound flooding from TC Idai, increased amounts of rainfall led to the largest increase in the flood hazard, which can be explained by the flooding being largely driven by the high river discharges (Eilander et al., 2023a). On the other hand, increased coastal flooding due to intensified wind speeds and SLR resulted in the largest increase in total damage, specifically in the coastal areas. The coastal areas are most densely inhabited – especially the coastal city of Beira – which explains the large effect of intensified wind speeds and SLR on impact despite their relatively small effect on the flooding itself, emphasizing the role of exposure and vulnerability. In terms of changes in relative damage, all flood drivers contribute significantly; buildings outside of Beira are also substantially damaged but have a lower total asset value.

Our results show that propagating the effects of climate change from hazard to impact influences the attribution assessment. Firstly, focussing on a single flood driver may not give a good representation of the total impact of climate change for the event. For compound flooding, it is important to consider the dynamic interactions of the multiple flood drivers (Green et al., 2025). Treating compound drivers independently may provide incomplete and incorrect attribution statements, underestimating the impact of climate change (Perkins-Kirkpatrick et al., 2024). The relative contribution of compound processes in TC-induced flooding becomes even more important in future climates (Grimley et al., 2024). Secondly, climate attribution results in different statements about the effect of climate change than impact attribution, which is explained by the



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non-linear relationship between flood hazard and damages (e.g. Moel et al., 2016; Pistrika et al., 2014). This highlights the relevance of including both climate and impact attribution assessments for describing the impacts of climate change. Together, they provide comprehensive information to inform risk management and adaptation strategies (Carlson et al., 2024; Clarke et al., 2023; Coumou et al., 2024).

Our attribution framework is applicable to TC events anywhere on earth and could easily be extended to other type of flood events. Since the framework solely requires global datasets and open-source software, it has great potential to address the attribution gap and analyse climate impact on flood events in underrepresented, data-poor, yet severely impacted and highly vulnerable regions. This study highlights once again the value and need for observations to improve and validate model results, such as in situ rain and tide gauges (Mekonnen et al., 2023). For areas with limited observational data, attribution statements should go hand in hand with a thorough uncertainty analysis. Echoing e.g. Eilander et al. (2023a) and Samadi et al. (2025), establishing high-quality observations should remain a priority for more accurate assessments in data-scarce regions and for providing more localized information on climate change impacts.

Our framework is built on simplified and uniform assumptions on the effect of climate change on TC rainfall and wind speed. The counterfactual rainfall is homogenously scaled according to the conservative Clausius—Clapeyron relationship and neglects any changes in spatio-temporal patterns (Deng et al., 2025; Kim et al., 2022; Liu et al., 2019). The counterfactual maximum wind speed reduction of 10 % also neglect the complex dynamics of TCs and may overestimate the climate change-increased coastal flooding (Knutson et al., 2020). The development of the counterfactual scenarios could be improved by further refining climate change trends in flood drivers, for example based on observed regional changes rather than global estimates. Moreover, we could evaluate the effect of climate change on additional flood drivers, such as change in TC size (Yamada et al., 2017), translation speed (Knutson et al., 2020; Seneviratne et al., 2021) and significant wave height (Thompson et al., 2021), which could also increase coastal flooding. As demonstrated by Dullaart et al. (2024) and Grimley et al. (2024), it is also possible to develop storyline approaches where the counterfactual is informed by TC statistics from pseudo global warming simulations. A promising but still developing method to construct comprehensive TC counterfactuals is the use of climate storyline simulations (Athanase et al., 2024b; Feser and Shepherd, 2025; Sánchez-Benítez et al., 2022). These simulations are nudged towards observed dynamics and can compare counterfactual realisations of near-real-time events. This method has been proven successful for mid- and high-latitude storms but is thus far limited for TCs due to the stronger role of convective processes (Athanase et al., 2024a; Goulart et al., 2024; Schubert-Frisius et al., 2017).

Our impact attribution is based on the calculation of damages to buildings using a simple but commonly used relationship between flood depth and damage. This method could be improved using multivariate depth damage curves that account for local characteristics of building types (Strauss et al., 2021) and other variables than flood depth influencing flood hazard such as duration, velocity, salinity or contamination (Adeke and Mugume, 2025; Delgado et al., 2016; Thieken et al., 2005). Impact



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attribution could be improved by including additional metrics of direct impacts, such as the displaced population (Mester et al., 2023); multi-hazard impacts, such as combined wind and flood damage (Wagenaar et al., 2018b); and indirect impacts, such as loss of livelihood options (Nhundu et al., 2021). Additionally, including dynamic changes in exposure and vulnerability, next to changes in the hazard, can improve our assessment of flood impact drivers. For example, the rising exposure and vulnerability in sub-Saharan Africa are found to increase damages from river flooding (Sauer et al., 2021). Such changes in exposure and vulnerability can be induced by climate change, but also by non-climatic drivers (Hope et al., 2022) such as land use change, urbanisation, or population growth (Paprotny et al., 2025; Rentschler et al., 2023; Rogers et al., 2025; Rogger et al., 2017). Lastly, total and relative damage provide different but incomplete perspectives on climate change impacts and we therefore recommend impact attribution to provide population differentiated assessments reflecting socio-spatial characteristics, such as age, gender and poverty (Puig et al., 2025). Differentiated assessments require a thorough understanding of the impacted population; studying population characteristics and their intersectionality as well as their response to different impact metrics. Such assessment can inform equitable and just adaptation measures to improve local resilience at the risks of climate change (Kind et al., 2017).

#### **5** Conclusion

Our study advances climate and impact attribution of compound flooding from TCs by providing a framework that physically resolves multiple flood drivers (rainfall, river discharge, tide, surge and waves) using a state-of-the-art modelling chain. Our framework was applied to TC Idai, that devastated Mozambique in March 2019, and was shown to accurately reproduce compound flooding. We demonstrate that considering multiple flood drivers enables a comprehensive view on the impacts of climate change. For the case of TC Idai, we find that propagating the effects of climate change from hazard to impact affects the outcome of an attribution assessment, due to the non-linear relationship between flood hazard and damages. The attribution analysis shows that 9 % of the flood volume, 2 % of the flood extent, and 31 % of the damages can be attributed to climate change. The amplification from change in hazard to impact can be linked to the majority of the damages occurring near the city of Beira, where coastal flooding was increased by wind and sea level rise. Our framework is applicable for TC-prone regions across the globe, including data-poor but highly impacted and vulnerable regions, potentially contributing to addressing the attribution gap.

Storyline attribution improves the description of how climate change-exacerbated flood drivers translate from hazard to impacts, which is relevant for anticipating further climate risks. Including the local context through the propagation to impact for specific extreme events has the potential to improve awareness by aligning closely with the lived experience of society. Our findings are sensitive to the applied impact metrics and simplified assumptions of the climate change effect on TC-induced flood drivers. Uncertainties in factual and counterfactual forcing persist in regions with a lack of long-term good quality observations, and stresses the ongoing priority for more observations and thorough uncertainty analyses. In the light of ongoing

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and intensifying climate change, we recommend research efforts to focus on extending climate to impact attribution for other highly impacted and vulnerable areas, and different type of compound events.

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.17107289 (Vertegaal et al., 2025).

400 Author contribution

DV, BvdH, AC, and SM conceived the idea for this study, jointly designed the experiments, and interpreted initial results. DV executed the experiments and set up the SFINCS, wflow and D-Flow FM models with help from NA, TB, and AC; NA helped with testing and setting up the D-Flow FM model; TB and AC helped with testing and setting up the wflow and SFINCS models; DV set up the Delft-FIAT model. FG and TL provided the necessary SnapWave simulations. DV conducted the computational processing and analysis of results with input from HMG and AC. DV wrote the manuscript with input from BvdH, AC, HMG, and SM.

**Competing interests** 

The authors declare that they have no conflict of interest.

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