



Hazard and Impact Synthesis and Attribution for Phase II use case

Deliverable 4.2

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Executive summary

This report presents the second phase of the COMPASS compound event attribution studies, building on the framework and findings established in Phase 1 to test, refine and extend operational climate attribution methods across seven use cases. Four use cases were extended from Phase 1 (UK Winter Storms, UK Drought-Heatwave, Tropical Cyclones Idai (East Africa) and Iota/Eta (Honduras)) with improved modelling frameworks and alternative attribution methods, while three new use cases (USA Tropical Cyclones, Durban floods and Crete Drought) were added to broaden the range of hazards and mechanisms covered by COMPASS.

Across this variety of use cases, climate change was consistently identified as a detectable, though generally modest, contributor to observed impacts. The size of its contribution varied: sea level rise accounted for an estimated 2-4% of US hurricane damages, climate change contributed 9-12% of flood damages in Durban, and it increased flood volume by 11% during Tropical Cyclone Idai. Several use cases (UK Winter Storms, Tropical Cyclone Idai and Honduras) showed stronger climate signals in Phase 2 than in Phase 1, reflecting the differences emerging from changes in model resolution and methodology, rather than a change in the underlying event. At the same time, non-climate factors such as exposure growth, land-use change, deforestation, infrastructure vulnerabilities and water management practices repeatedly emerged as a major driver of impacts. This was particularly evident in the Crete use case, where water scarcity was found to primarily originate from land-use change and irrigation expansion rather than climate alone.

Phase 2 also taught important methodological lessons. High resolution inputs (convection-permitting climate models, refined Digital Elevation Models and land cover data) consistently improved the accuracy and robustness of attribution results, while global or coarser datasets introduce significant uncertainty. The comparison of storyline-based methods (DestinE spectrally-nudged climate simulations) against more simplified, established approaches (Clausius-Clapeyron scaling) showed broadly consistent results but revealed that nudged storyline data still carry limitations in isolating thermodynamic climate signals from spatial and model uncertainty, a finding that recurred across different use cases with different event types (TC Idai and Durban floods). Cascading and indirect impacts, such as antecedent soil saturation, drought-induced infrastructure damage, and socio-economic vulnerability, remained difficult to capture within current modelling frameworks, and the choice of event definition and flood thresholds was shown to affect attribution outcomes.

Taken together, Phase 2 demonstrates the growing maturity and policy relevance of the COMPASS attribution framework, while underscoring the continued need for higher-resolution data, multi-method validation, and stronger integration of non-climate drivers to ensure attribution results are robust, transparent, and actionable for adaptation planning.

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1. Introduction

The overarching goal of COMPASS is to develop a harmonised, yet flexible, methodological framework for climate and impact attribution of complex extreme events, including compound, sequential and cascading hazards. The first phase of the COMPASS Use Cases (UCs), reported in Deliverable 4.1, established and tested this framework across five different events and geographical contexts: Storm Xynthia in France (2010), the UK winter storms in Somerset (2013-2014), the UK drought-heatwave affecting Luton airport (2022), Tropical Cyclones Idai and Kenneth in East Africa (2019), Tropical Cyclone Freddy in East Africa (2023), and Tropical Cyclones Eta and Iota in Honduras (2020).

Phase 1 demonstrated that a shared methodological framework, combining probabilistic (risk-based) and storyline-based attributions approaches, could be adapted to a wide range of institutional contexts and data environments while still benefiting from common code, modelling components and datasets. Across the UCs, climate change consistently emerged as a significant, even if sometimes uncertain, driver of observed impacts. Non-climatic factors such as population exposure, economic growth, or societal challenges (e.g. violence, pandemics) were shown to critically shape how those impacts truly materialized. These findings underscored both the feasibility of moving towards operational attribution and the need for a more holistic approach of vulnerability and socio-economic contexts surrounding natural hazards.

The concluding synthesis of D4.1 identified several priority areas for advancement in a second phase of the UCs: refinement of hazard and impact modelling frameworks (including defenses representation, resolution, and bias correction); more robust, locally specific vulnerability modelling; stronger integration of qualitative and quantitative attribution approaches; systematic testing of the sensitivity of results to methodological choices such as attribution method and baseline period; and a deeper focus on translating results into policy-relevant outputs.

Phase 2 aims to answer those questions through two complementary lines of work. First, four of the Phase 1 UCs have been extended to deepen and diversify the original analysis:

- The UK winter storms UC has been extended to test an alternative storyline-based approach using UKCP Local Projections in place of HadGEM3-A and different hydrological model configurations. With a 2.2km resolution, this convection-permitted model allows for a better representation of precipitation than the previous model (60km resolution for HadGEM3-A). Instead of the former UC using a probabilistic method made of 300 factual and counterfactual simulations, this extension only uses three simulations; with different time slices and adding another counterfactual dimension corresponding to a warmer “+3°C world”.
- The UK drought-heatwave UC has been extended from aviation to the rail network to reflect the spatially compounding aspect of this event. Using a novel modeling approach and new climate data from Destination Earth, this storyline-based extension helps support a more complete understanding of the event’s contribution to long-term adaptation and resilience planning across various transport infrastructures.
- The Tropical Cyclones Idai flooding UC in Sofala (Mozambique) has been revisited to explore an alternative attribution method based on the nudged climate storylines dataset from the Destination Earth ClimateDT project, testing these factual and counterfactual scenarios for a major historical flood event. This aims to establish whether flood hazard modelling for individual extreme events can be robustly performed using ClimateDT storylines, and to build understanding of the uncertainty associated with this method.
- The Tropical Cyclones Eta and Iota flooding UC in Honduras has been extended by refining the hazard modeling framework, following the need from Phase 1 of more accurate flood simulations. To do so, the

same methodology is used with several improvements in the representation of topography, model domain, land cover, and surface roughness.

Second, Phase 2 introduces three new UCs selected to broaden the range of hazard types and geographical contexts covered by COMPASS:

- Tropical cyclone-driven asset losses in the United States between 1996 and 2024, attributing physical asset losses from 104 tropical cyclones and 5,042 county-cyclone pairs across 224 counties on the U.S. Atlantic and Gulf Coasts to sea level rise.
- The 2022 eThekweni floods and landslides in South Africa, examining the catastrophic rainfall event of 11–12 April 2022 in KwaZulu-Natal and eThekweni (with a specific focus on Durban), compounded by a further storm on 21 May 2022, and its disproportionate impact on informal settlements already weakened by prior storms and the COVID-19 pandemic.
- The Crete Drought (Tympaki Basin, 1980–2022) use case examines how long-term climate variability, land-use change, and water management drove chronic water scarcity in a 265 km² agricultural basin. Unlike other COMPASS cases, this focuses on long-term, cumulative drought rather than isolated extreme events, emphasizing systemic vulnerability in a Mediterranean agricultural basin.

Together, these extended and new use cases allow COMPASS to test the refined methodological framework against a wider diversity of hazard mechanisms, spatial scales, and vulnerability contexts, while directly addressing the methodological and analytical gaps identified in Phase 1.

1.1. Overview of use cases phase II

The use cases are summarized in the Table 1 below including the geography, types of hazards and compounding, and attribution method. For the classification of compounding events, we draw on the typology of Zscheischler et al. (2020)¹.

Table 1: Overview of the COMPASS Use Cases (UCs)

Name and date	Considered in Phase 1	Geography	Hazards	Compounding	Attribution method	Lead institution
UC1 – USA tropical cyclones	no	USA (Atlantic and Gulf coasts)	Storm surge, Wind, rainfall	Temporal, spatial	Probabilistic	PIK
UC2a – United Kingdom winter storms (2013/2014) extended	yes	United Kingdom, Somerset	Rainfall, wind, storm surge, flooding (fluvial, pluvial, coastal)	Multivariate, temporal	Storyline	Deltares and Met Office
UC2b – United Kingdom drought heatwave (2022/2023) extended	yes	United Kingdom (Eastern and Central England)	Drought, Heat	Multivariate, spatial	Storyline	Met Office

¹ Zscheischler, J., Martius, O., Westra, S., Bevacqua, E., Raymond, C., Horton, R. M., ... & Vignotto, E. (2020). A typology of compound weather and climate events. *Nature reviews earth & environment*, 1(7), 333-347.

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UC3 – East Africa Tropical Cyclone Idai (2019) extended	yes	Mozambique (Sofala)	Wind, storm surge, rainfall, flooding (fluvial, pluvial, coastal)	Multivariate, Spatial	Storyline	Deltares
UC4 – Tropical storms Eta and Iota (2020) extended	yes	Honduras (Sulla Valley, Cortès)	Rainfall, flooding (fluvial, pluvial), COVID-19, violence	Multivariate (non-climate), temporal	Storyline (quantitative and qualitative)	Red Cross Red Crescent Climate Centre and Deltares
UC5 – Durban cut off low flooding (2022)	no	South Africa (eThekweni, KwaZulu-Natal)	Rainfall, flooding, mud- and landslides	Multivariate, spatial, temporal	Probabilistic	Deltares and Red Cross Red Crescent Climate Centre
UC6 – Crete drought (2025)	no	Crete, Greece	Consecutive and prolonged drought events 1980-2022	Multivariate, temporal	Physical-based system modeling	Seven, PIK

2. Use Case 1: USA tropical cyclones

2.1. Summary of the events

In this use case, we attribute physical asset losses from 104 tropical cyclones² (TCs) in the conterminous United States between 1996 and 2024 to sea level rise (SLR). The criterion for the selection of tropical cyclones is that they have caused storm surge inundation in at least one county, identified based on modelled storm surge data and its spatial overlap with assets maps. In total 5,034 county-cyclone pairs from 224 counties are considered. All assessed tropical cyclones formed in the Atlantic Basin and made landfall on the U.S. Atlantic and Gulf Coasts (Figure 1 and Figure 2).

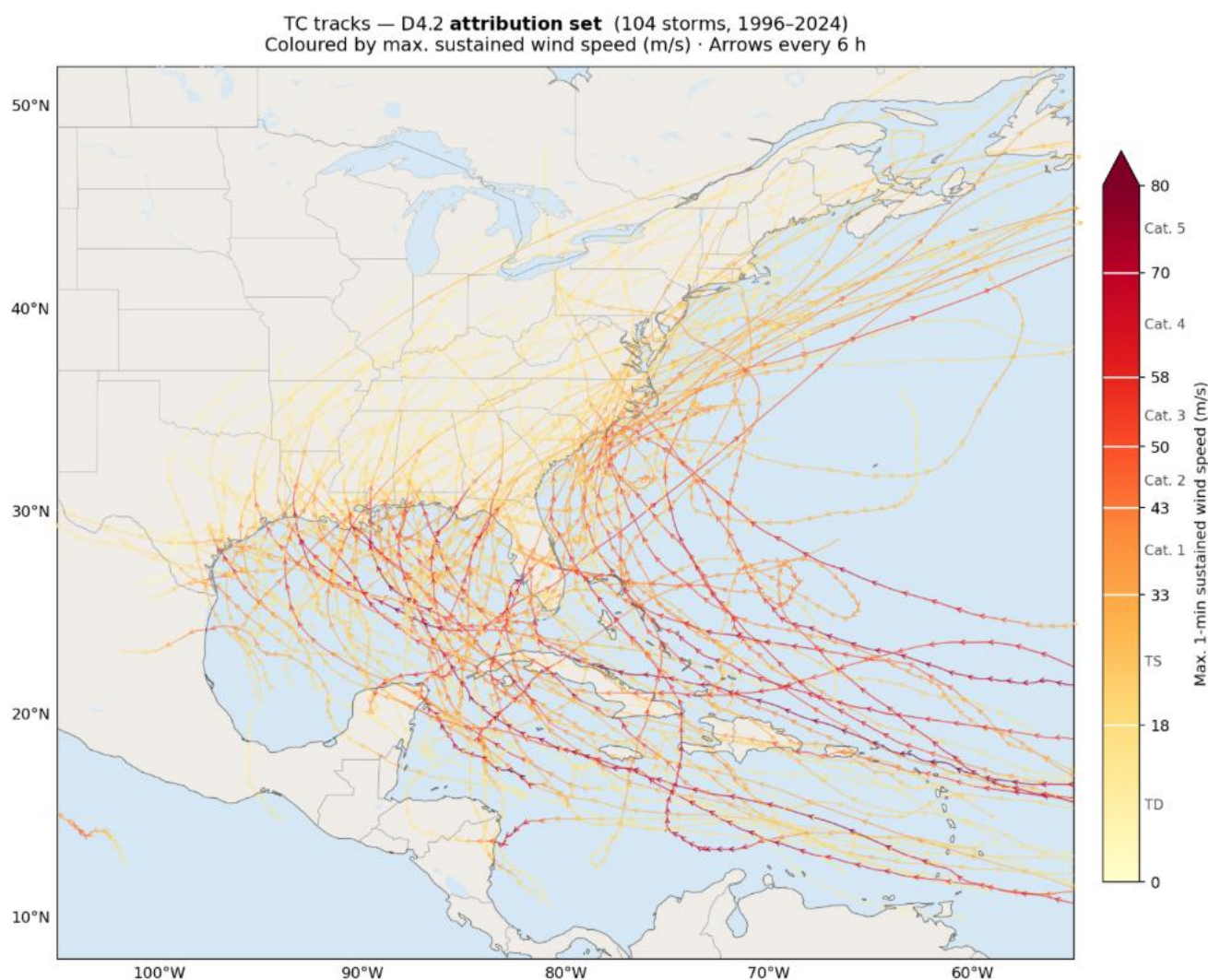


Figure 1: Tracks of the 104 tropical cyclones considered in this study (1996–2024). Track segments are colored by the maximum 1-minute sustained wind speed (m/s) at each position along the track; arrows mark 6-hourly track positions and indicate the direction of tropical cyclones' motion. Additionally, the Saffir–Simpson Hurricane Wind Scale³ categories are indicated in the color bar (TD: tropical depression; TS: tropical storm; Cat. 1–5:

² Tropical cyclones in the North Atlantic and the central and eastern North Pacific that reached a maximum one-minute sustained wind speed of at least 64 kn are called hurricanes. For consistency within this document, we, however, only use the term *tropical cyclone*.

³ <https://www.nhc.noaa.gov/aboutsshws.php>

hurricane categories 1–5). Track data is provided by the International Best Track Archive for Climate Stewardship⁴ (IBTrACS).

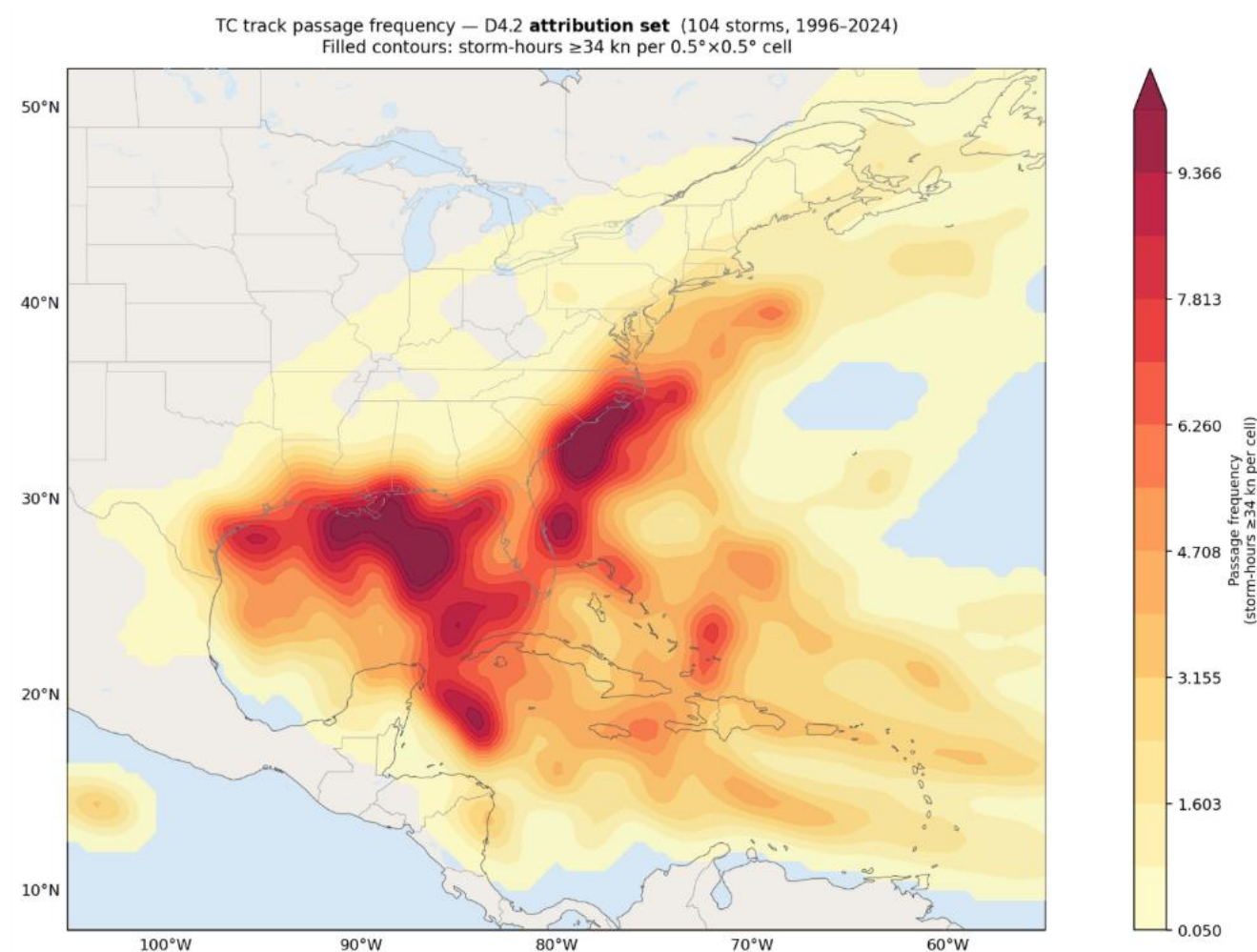


Figure 2: Passage frequency of the 104 tropical cyclones assessed in this study (1996–2024). Shading represents the cumulative number of hourly track positions with maximum sustained wind speeds ≥ 34 kn (tropical storm intensity or above³) per $0.5^\circ \times 0.5^\circ$ grid cell, smoothed with a Gaussian kernel ($\sigma \approx 0.8^\circ$). Grid cells with fewer than 0.05 storm-hours are masked. Track data is provided by IBTrACS⁴.

2.2. Observed hazards

2.2.1. Type of hazards

This use case models tropical cyclone damage based on wind, rainfall and storm surge hazards. We only consider hazard intensities if they reached hazardous levels, i.e. we set values below a certain threshold to zero (see Section 2.4.1). In addition, hazard intensities only feed into the county-specific hazard indicator if they spatially intersect with exposed economic assets (assessed on a grid cell level).

2.2.2. Form of compounding

In our modeling, we account for compounding wind, rainfall, and coastal flooding. (see Section 2.4.2). We allow for the county-level wind and rain indicator to be zero. The storm surge indicator, however, must always be

⁴Knapp, K. R., Kruk, M. C., Levinson, D. H., Diamond, H. J., & Neumann, C. J. (2010). The International Best Track Archive for Climate Stewardship (IBTrACS): Unifying tropical cyclone best track data, B. *Bulletin of the American Meteorological Society*, 91, 363–376,. <https://doi.org/10.1175/2009BAMS2755.1>

greater than zero, since we are interested in the sea-level rise signal. To this end, we include county-level events where one (storm surge), two (storm surge + wind or rain) or all three hazards are present.

2.2.3. Driving dynamics

North Atlantic basin climatology. The North Atlantic is one of seven major ocean basins where tropical cyclones occur. Between 1991 and 2020, an average of 14 named storms (sustained winds ≥ 34 kt) formed per season, including 7 that reached hurricane strength (≥ 64 kt) and 3 major hurricanes (Category 3 or higher, ≥ 96 kt)^{3,5}. TC activity in the North Atlantic shows strong interannual and multidecadal variability. Interannual fluctuations are mainly driven by the El Niño–Southern Oscillation (ENSO), with La Niña phases leading to increased TC activity due to reduced vertical wind shear in the Main Development Region (MDR). On longer timescales (30–80 years), variability is dominated by the Atlantic Multidecadal Oscillation (AMO): Warm phases of the AMO are associated with increased TC frequency and intensity due to warmer sea surface temperatures and decreased vertical wind shear in the MDR⁶.

Climate Change. Under ongoing warming, TC-induced flooding is projected to worsen due to rising sea levels and an intensification of TC-induced rainfall, since warmer air can hold more moisture^{7,8}. Further, warmer ocean surface temperatures favor the creation of larger and more intense cyclones. Therefore, the share of severe tropical cyclones will likely increase due to human-made climate change (see Knutson et al. 2020⁹ for a recent structured literature review).

Tropical cyclone exposure. Over the past decades, population and economic growth in coastal regions have significantly increased human exposure to the hazards of tropical cyclones¹⁰. This trend is projected to continue under future socioeconomic scenarios¹¹.

2.2.4. Intensity/Extremity/Magnitude

The assessed set of tropical cyclones includes events from all the categories of the Saffir-Simpson Hurricane Wind Scale³ (excl. Tropical Depressions; see Table 2). In consequence, the tropical cyclones considered can differ largely with respect to intensity and size. This is also represented in the wind, rain, and storm surge footprints.

⁵ *Tropical Cyclone Climatology*. (n.d.). Retrieved May 5, 2026, from <https://www.nhc.noaa.gov/climo/>

⁶ Bell, G. D., & Chelliah, M. (2006). *Leading Tropical Modes Associated with Interannual and Multidecadal Fluctuations in North Atlantic Hurricane Activity*. *Journal of Climate*, 19(4), 590–612. <https://doi.org/10.1175/JCLI3659.1>

⁷ Masson-Delmotte, V., Zhai, P., Pirani, A., Connors, S. L., Péan, C., Berger, S., Caud, N., Chen, Y., Goldfarb, L., Gomis, M. I., Huang, M., Leitzell, K., Lonnoy, E., Matthews, J. B. R., Maycock, T. K., Waterfield, T., Yelekçi, Ö., Yu, R., & Zhou, B. (Eds.). (2021). *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press. <https://doi.org/10.1017/9781009157896>

⁸ Pörtner, H.-O., Roberts, D. C., Tignor, M. M. B., Poloczanska, E. S., Mintonbeck, K., Alegría, A., Craig, M., Langsdorf, S., Löschke, S., Möller, V., Okem, A., & Rama, B. (Eds.). (2022). *Climate Change 2022: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. <https://doi.org/10.1017/9781009325844>

⁹ Knutson, T., Camargo, S. J., Chan, J. C. L., Emanuel, K., Ho, C.-H., Kossin, J., Mohapatra, M., Satoh, M., Sugi, M., Walsh, K., & Wu, L. (2020). *Tropical Cyclones and Climate Change Assessment: Part II: Projected Response to Anthropogenic Warming*. *Bulletin of the American Meteorological Society*, 101(3), E303–E322. <https://doi.org/10.1175/BAMS-D-18-0194.1>

¹⁰ Emanuel, K. (2005). *Increasing destructiveness of tropical cyclones over the past 30 years*. *Nature*, 436(7051), 686–688. <https://doi.org/10.1038/nature03906>

¹¹ Gettelman, A., Bresch, D. N., Chen, C. C., Truesdale, J. E., & Bacmeister, J. T. (2018). *Projections of future tropical cyclone damage with a high-resolution global climate model*. *Climatic Change*, 146(3–4), 575–585. <https://doi.org/10.1007/s10584-017-1902-7>

One of the most destructive and most known tropical cyclones featured in this study is Hurricane Katrina (2005). As an example, its hazard footprints are shown in Figure 3 to Figure 5. Footprints for all other tropical cyclones considered in this study, as well as other supplementary materials, can be interactively browsed on this website: https://www.pik-potsdam.de/~janhasel/compass_d4.2/.

Table 2: Tropical cyclone count per Saffir–Simpson Hurricane Wind Scale category. Storm names and years of occurrence are listed per category. The dataset spans 1996–2024 and covers all tropical cyclones for which wind speed, rainfall, and storm surge hazard indicators were computed and for which at least one county-level storm surge indicator exceeds 0. See Section 2.4 for the definition of county-level hazard indicators.

Category	Count	Storm names (year)
Cat. 5	10	Isabel (2003), Ivan (2004), Katrina (2005), Rita (2005), Wilma (2005), Matthew (2016), Irma (2017), Michael (2018), Ian (2022), Beryl (2024)
Cat. 4	20	Nora (1997), Georges (1998), Floyd (1999), Michelle (2001), Lili (2002), Charley (2004), Frances (2004), Dennis (2005), Gustav (2008), Ike (2008), Earl (2010), Harvey (2017), Jose (2017), Florence (2018), Delta (2020), Eta (2020), Laura (2020), Ida (2021), Idalia (2023), Helene (2024)
Cat. 3	9	Bertha (1996), Fran (1996), Bonnie (1998), Isidore (2002), Alex (2004), Jeanne (2004), Irene (2011), Sandy (2012), Zeta (2020)
Cat. 2	10	Earl (1998), Dennis (1999), Irene (1999), Gustav (2002), Dolly (2008), Ida (2009), Alex (2010), Arthur (2014), Sally (2020), Francine (2024)
Cat. 1	19	Danny (1997), Claudette (2003), Gaston (2004), Cindy (2005), Ophelia (2005), Ernesto (2006), Humberto (2007), Hanna (2008), Isaac (2012), Hermine (2016), Nate (2017), Barry (2019), Hanna (2020), Isaias (2020), Elsa (2021), Henri (2021), Nicholas (2021), Nicole (2022), Debby (2024)
Trop. Storm	36	Arthur (1996), Charley (1998), Frances (1998), Hermine (1998), Harvey (1999), Helene (2000), Allison (2001), Barry (2001), Bertha (2002), Fay (2002), Hanna (2002), Bill (2003), Grace (2003), Bonnie (2004), Matthew (2004), Arlene (2005), Alberto (2006), Barry (2007), Edouard (2008), Fay (2008), Claudette (2009), Bonnie (2010), Hermine (2010), Lee (2011), Beryl (2012), Debby (2012), Andrea (2013), Bill (2015), Colin (2016), Cindy (2017), Emily (2017), Gordon (2018), Fred (2021), Mindy (2021), Harold (2023), Ophelia (2023)
Total	104	

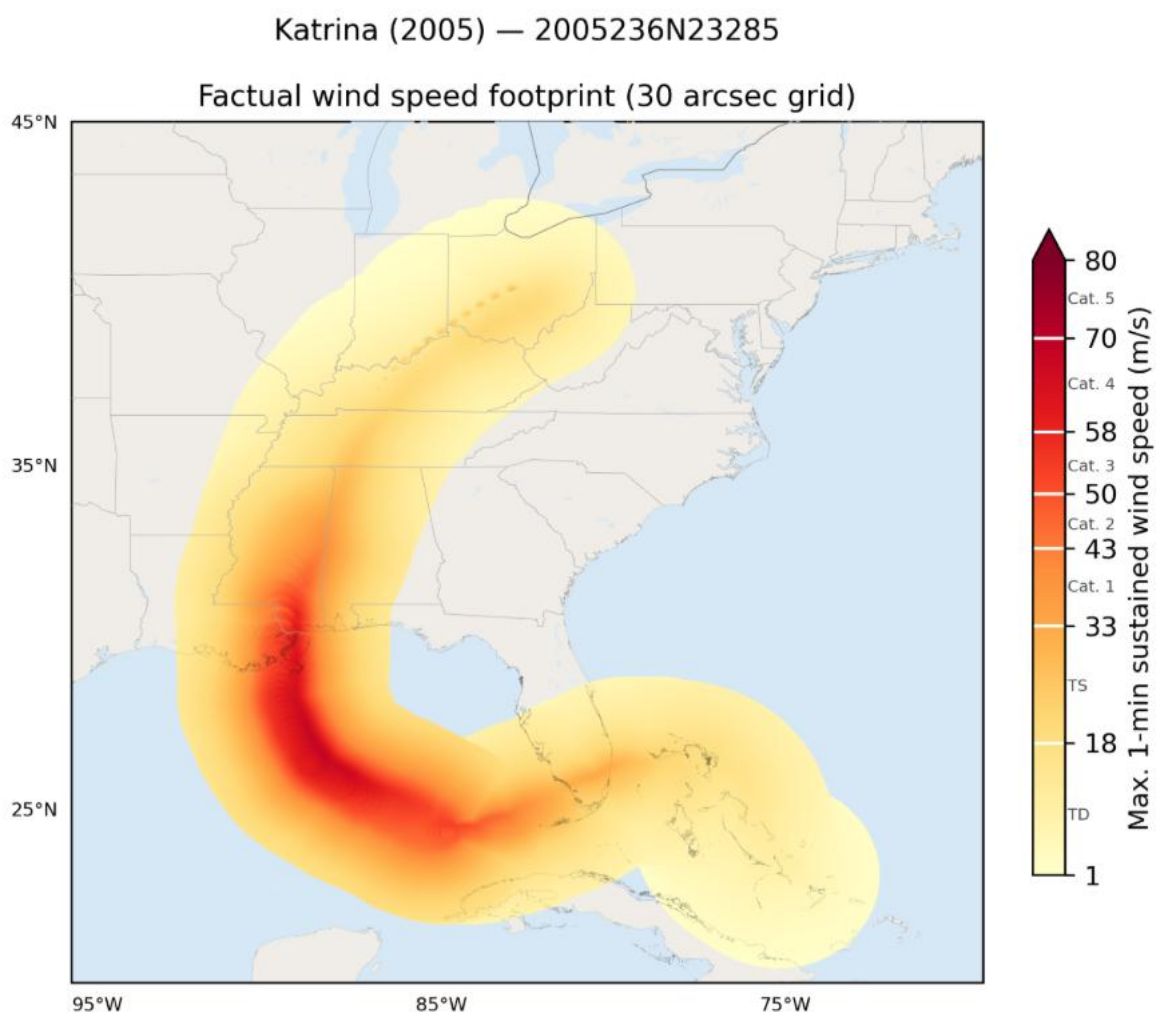


Figure 3: Exemplary wind footprint of Hurricane Katrina, in terms of maximum 1-minute sustained wind speed (m/s) per 30 arcsecond grid cell. Wind fields are modelled by applying IBTrACS⁴ track data to Holland's Revised Hurricane Pressure-Wind Model¹². Grid cells with a value below 1 m/s are masked out. The color bar is annotated with the Saffir–Simpson Hurricane Wind Speed³ categories (TD: tropical depression; TS: tropical storm; Cat. 1–5: hurricane categories 1–5). Wind footprints for all other tropical cyclones can be found at https://www.pik-potsdam.de/~janhasel/compass_d4.2/wind_maps/.

¹² Holland, G. (2008). A Revised Hurricane Pressure–Wind Model. Monthly Weather Review, 136(9), 3432–3445. <https://doi.org/10.1175/2008MWR2395.1>

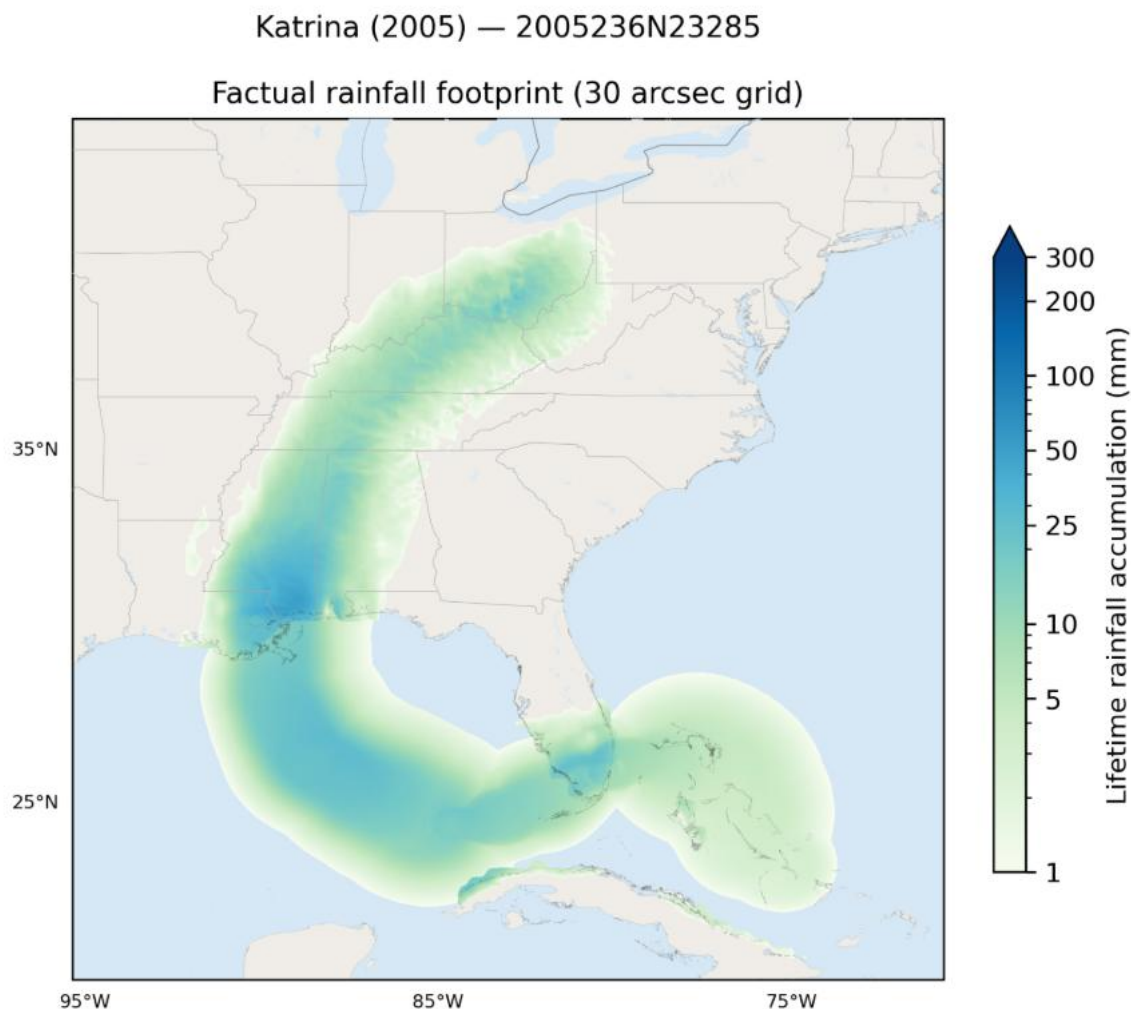


Figure 4: Exemplary rain footprint of Hurricane Katrina, in terms of lifetime rainfall accumulation (mm) per 30 arcsecond grid cell. Rain fields are modelled by applying IBTrACS track data⁴ to the TCR model^{13,14}. Grid cells with a value below 1 mm are masked out. Rain footprints for all other tropical cyclones can be found at https://www.pik-potsdam.de/~janhasel/compass_d4.2/rain_maps/.

¹³ Lu, P., Lin, N., Emanuel, K., Chavas, D., & Smith, J. (2018). Assessing Hurricane Rainfall Mechanisms Using a Physics-Based Model: Hurricanes Isabel (2003) and Irene (2011). *Journal of the Atmospheric Sciences*, 75(7), 2337–2358. <https://doi.org/10.1175/JAS-D-17-0264.1>

¹⁴ Feldmann, M., Emanuel, K., Zhu, L., & Lohmann, U. (2019). Estimation of Atlantic Tropical Cyclone Rainfall Frequency in the United States. *Journal of Applied Meteorology and Climatology*, 58(8), 1853–1866. <https://doi.org/10.1175/JAMC-D-19-0011.1>

Katrina (2005) — 2005236N23285

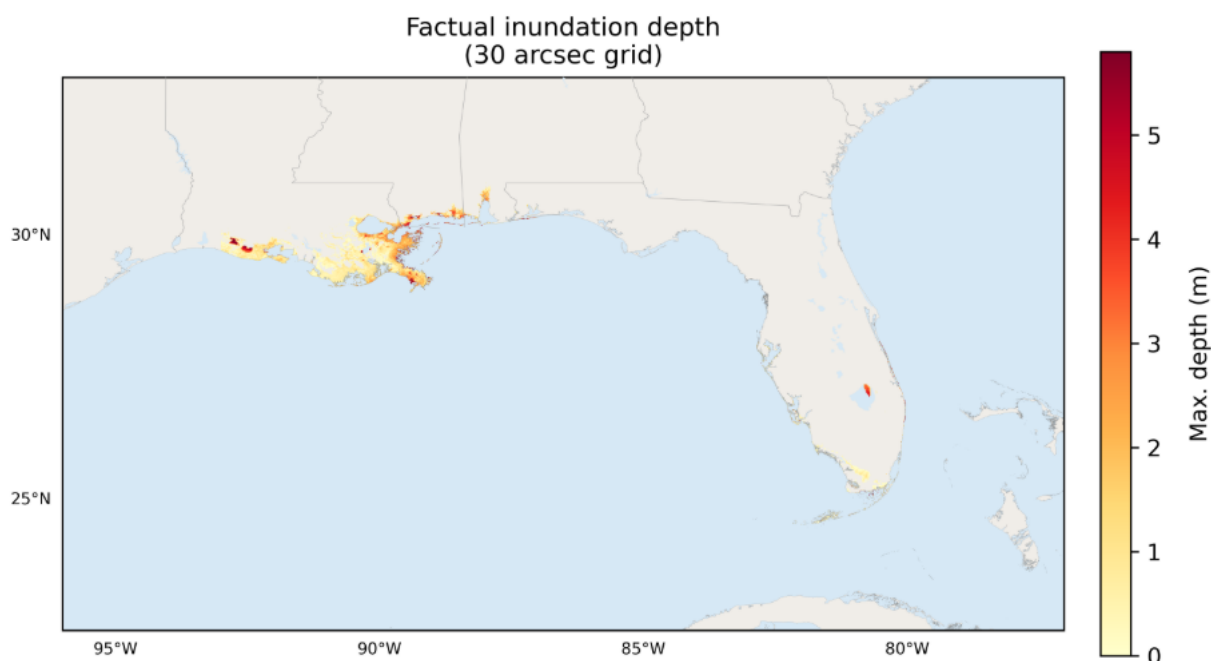


Figure 5: Exemplary storm surge footprint of Hurricane Katrina, in terms of maximum inundation depth (m). The inundation data set is provided by Mengel^{15,16}, modelled on a 30 arcsecond grid using the geophysical flow solver GeoClaw¹⁷. Storm surge footprints for all other tropical cyclones can be found at https://www.pik-potsdam.de/~janhasel/compass_d4.2/surge_maps/.

2.3. Observed impacts

2.3.1. Quantitative impacts

This study draws on 1,271 coastal, county-level tropical cyclone damage events, spanning 206 counties and 100 tropical cyclones between 1996 and 2024¹⁸. Together, these events represent USD 126.7 bn in reported damage, averaging USD 99.7 M per event. Most damage was caused around the Gulf coast and the Atlantic coast of Florida. The distribution of damage across events is highly skewed: The median event caused USD 500 k in damage, while the standard deviation amounts to USD 490.7 M. This underscores how strongly a small number of extreme events drive the total damage. Damage ranges from as little as USD 200 at the low end to USD 7.0 bn for the most destructive county-cyclone pair. Half of all events fell between USD 25 k (25th percentile) and USD 8.4 M (75th percentile), indicating that while most county-level impacts were comparatively moderate, the aggregate damage total is dominated by a limited number of catastrophic outliers (see Table 3).

¹⁵ Mengel, M. (2024). *Dataset of tropical cyclone-affected areas (D1.4)*, (Version v1.0). <https://doi.org/10.5281/ZENODO.14547984>

¹⁶ Mengel, M. (2025). *Counterfactual dataset of tropical cyclone-affected areas* (Version 1.0). ISIMIP Repository. <https://doi.org/10.48364/ISIMIP.693793>

¹⁷ Berger, M. J., George, D. L., LeVeque, R. J., & Mandli, K. T. (2011). *The GeoClaw software for depth-averaged flows with adaptive refinement*. *Advances in Water Resources*, 34(9), 1195–1206. <https://doi.org/10.1016/j.advwatres.2011.02.016>

¹⁸ National Centers for Environmental Information. (2026). *Storm Events Database*. Retrieved from <https://www.nci.noaa.gov/stormevents/>

Table 3: Quantitative impacts of the assessed set of county-cyclone pairs, as reported in the NCEI Storm Events Database¹⁸. Damage values are in nominal USD.

Statistic	Value
Observation period	1996–2024
Storm count	100
County-cyclone observations	1,271
Unique counties affected	206
Total reported damage	USD 126.7 bn
Mean damage per storm	USD 99.7 M
Median damage	USD 500 k
Std. dev. of damage	USD 490.7 M
Min. damage	USD 200
Max. damage	USD 7.0 bn
25th percentile	USD 25 k
75th percentile	USD 8.4 M

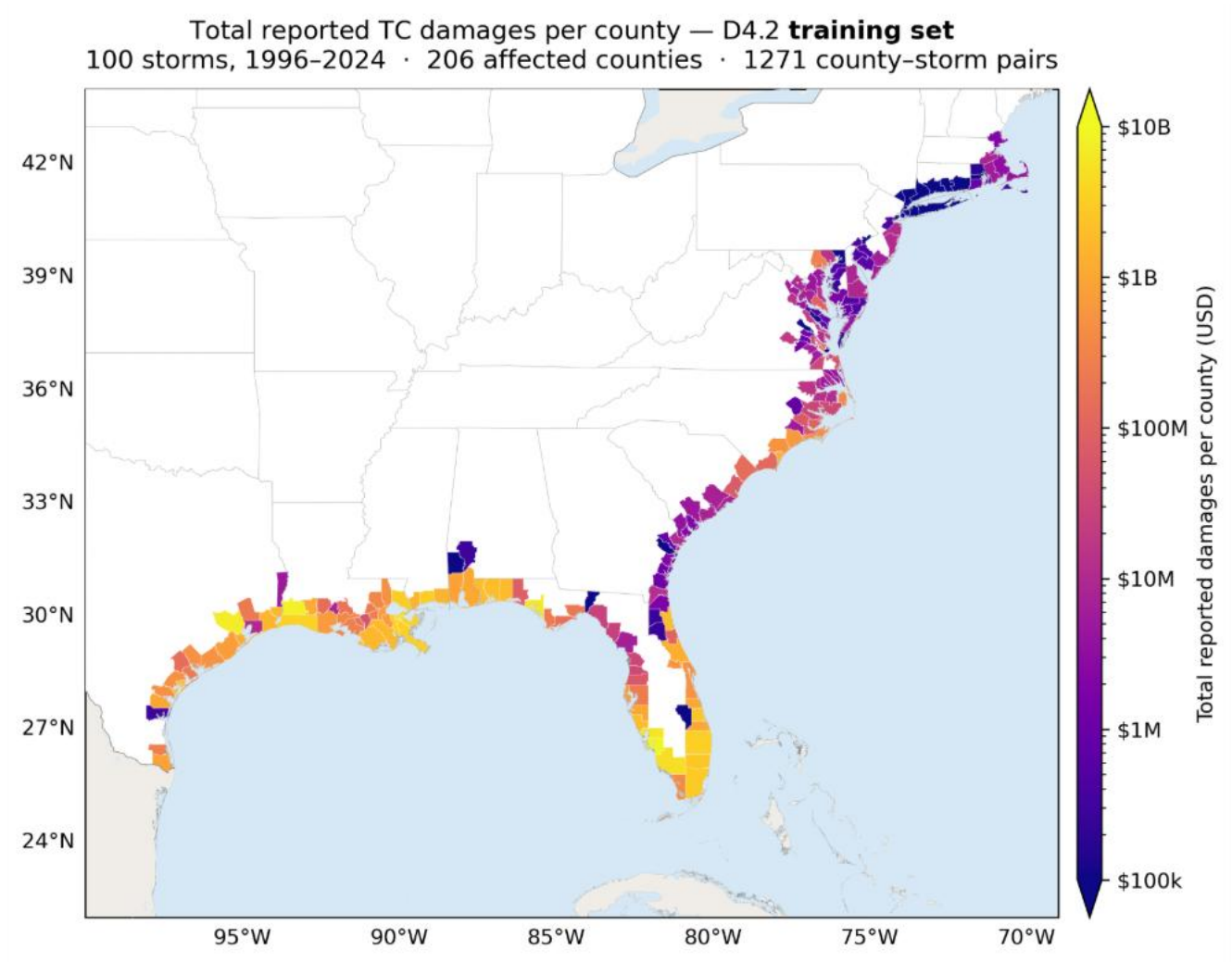


Figure 6: Total reported tropical cyclone damages per county, aggregated over the model training dataset (100 tropical cyclones, 1996–2024). Events (county-cyclone pairs) are only considered if the model indicates exposure to storm surge (1271 county-cyclone pairs, 206 affected counties). Damages correspond to property damage reported in the NCEI Storm Events Database¹⁸ (nominal USD).

2.3.2. Qualitative impacts and responses

We do not assess qualitative impacts and responses in this study.

2.4. Modeling framework

2.4.1. Hazard modeling

For the hazards wind, rain, and storm surge, we compute hazard indicators as the county-level, asset-weighted sum of (transformed) hazard intensity over all 30 arcsecond grid cells c falling within county i for tropical cyclone s :

$$X_{i,s} = \sum_{c \in i} k_{c,s} \cdot f(H_{c,s})$$

where $H_{c,s}$ is the raw hazard intensity at grid cell c and $k_{c,s}$ is the fixed asset value at that cell in the year of tropical cyclone s .

Hurricane wind fields are modelled from IBTrACS⁴ track data, applying Holland’s Revised Hurricane Pressure-Wind Model¹² to each track record on a 30-arcsecond grid using the CLIMADA TropCyclone module¹⁹. Grid cells with 1-minute sustained wind speeds below 17.5 m/s (the tropical storm threshold) are set to zero. The intensity transform f is Emanuel’s sigmoidal function²⁰:

$$f_{\text{sig}}(V) = \frac{v_n^3}{1 + v_n^3}, \quad v_n = \frac{\max(V - V_{\text{thr}}, 0)}{V_h - V_{\text{thr}}}$$

with threshold wind speed above which asset losses occur, $V_{\text{thr}} = 25.7$ m/s, and slope parameter $V_h = 112.0$ m/s. The former is the originally proposed and commonly used value, while the latter was calibrated in a previous study specifically for U.S. counties based on the same damage data set²¹. The sigmoidal function form captures the empirically observed behavior of wind-induced damage.

Gridded TC rainfall is simulated from the same track data using the TCR (Tropical Cyclone Rainfall) model^{13,14} implemented in the CLIMADA Petals TCRain module¹⁹. We use the lifetime rain indicator, defined as the total accumulated rainfall (mm) over the full TC passage at each grid cell. Grid cells receiving less than 25 mm lifetime accumulation are set to zero. The intensity transform is linear ($f(R) = R$).

Storm surge flood depths are provided by Mengel et al.^{15,16,22}, modelled on a 30 arcsec grid using the geophysical flow solver GeoClaw¹⁷. The data sets include factual data^{15,16}, reproducing observed conditions with present-day sea levels, counterfactual data with historical sea levels (sea-level rise removed)^{16,22}, as well as counterfactual data with 1m of relative sea level rise^{16,22}. We set grid cells with surge depths below 0.3 m to zero. We also set grid cells above 10 m to zero, as they likely represent numerical artefacts in the GeoClaw solver (the highest recorded US storm surge, from Hurricane Katrina in 2005, reached approximately 8.5 m²³). The intensity transform is linear ($f(S) = S$).

2.4.2. Impact modeling

We model county-cyclone damage as a function of the three county-level hazard indicators using a Poisson Pseudo-Maximum Likelihood (PPML) regression, i.e. a Poisson Generalized Linear Model with a log link:

$$\mathbb{E}[L_{i,s}] = \exp\left(\beta_0 + \beta_1 \ln(1 + W_{i,s}) + \beta_2 \ln(1 + R_{i,s}) + \beta_3 \ln S_{i,s}\right)$$

¹⁹ Gabriela Aznar Siguan, David N. Bresch, Samuel Eberenz, Jan Hartman, Marine Perus, Thomas Rösli, Dario Stocker, Veronica Bozzini, Carmen B. Steinmann, Evelyn Mühlhofer, Rachel Bungerer, Inga J. Sauer, Samuel Lüthi, Pui Man (Mannie) Kam, Simona Meiler, Alessio Ciullo, Thomas Vogt, Benoit P. Guillod, Chahan M. Kropf, ... Dahyann Araya. (2025). *CLIMADA Core Python Package* (Version v6.1.0). <https://doi.org/10.5281/ZENODO.17233409>

²⁰ Emanuel, K. A. (2011). *Global Warming Effects on U.S. Hurricane Damage*. *Weather, Climate, and Society*, 3(4), 261–268. <https://doi.org/10.1175/WCAS-D-11-00007.1>

²¹ Hassel, J., Vogt, T., Frieler, K., & Otto, C. (2025). *Poor and unequal US counties are more vulnerable to hurricane damage*. SSRN. <https://doi.org/10.2139/ssrn.5929136>

²² Mengel, M., Katja, F., Sauer, I., & Otto, C. (2025). *Counterfactual dataset of tropical cyclone affected areas*. <https://doi.org/10.5281/ZENODO.18391036>

²³ Fritz, H. M., Blount, C., Sokoloski, R., Singleton, J., Fuggle, A., McAdoo, B. G., Moore, A., Grass, C., & Tate, B. (2007). *Hurricane Katrina storm surge distribution and field observations on the Mississippi Barrier Islands*. *Estuarine, Coastal and Shelf Science*, 74(1), 12–20. <https://doi.org/10.1016/j.ecss.2007.03.015>

PPML is a consistent quasi-maximum likelihood estimator for any model of the form $E[L] = \exp(x\beta)$, irrespective of the true error distribution²⁴. Unlike ordinary least squares on log-transformed damage, it avoids the retransformation bias introduced by Jensen's inequality²³. Predictions are directly expressed in USD, making summations to annual totals straightforward and unbiased. PPML weights residuals in proportion to the predicted level rather than the log-deviation, which ensures that large events, which dominate aggregate annual losses, receive appropriate influence in the calibration.

The model is fitted on all county-cyclone pairs for which (i) reported damage is positive and (ii) the surge indicator is positive ($n = 1,271$ observations from 104 TCs, out of 112 TCs making landfall in the conterminous United States between 1996 and 2024). This surge criterion maximizes coverage for training the model: Every county-cyclone pair for which storm surge was relevant, according to the defined storm surge indicator, contributes a prediction, regardless of whether wind or rainfall indicators are simultaneously positive. Reported damages are taken from the NCEI Storm Events database¹⁸ and aggregated to the county level. Standard errors are reported using HC3 sandwich-robust estimates, which are valid under arbitrary heteroskedasticity and overdispersion. The estimated surge coefficient is $\theta_3 = +0.163$ (HC3 SE = 0.049; $p = 0.001$); the model achieves a leave-one-out cross-validated R^2 of 0.36 (on a cyclone-by-cyclone basis) and near-perfect aggregate calibration (sum of predicted / sum of reported = 1 across the full dataset).

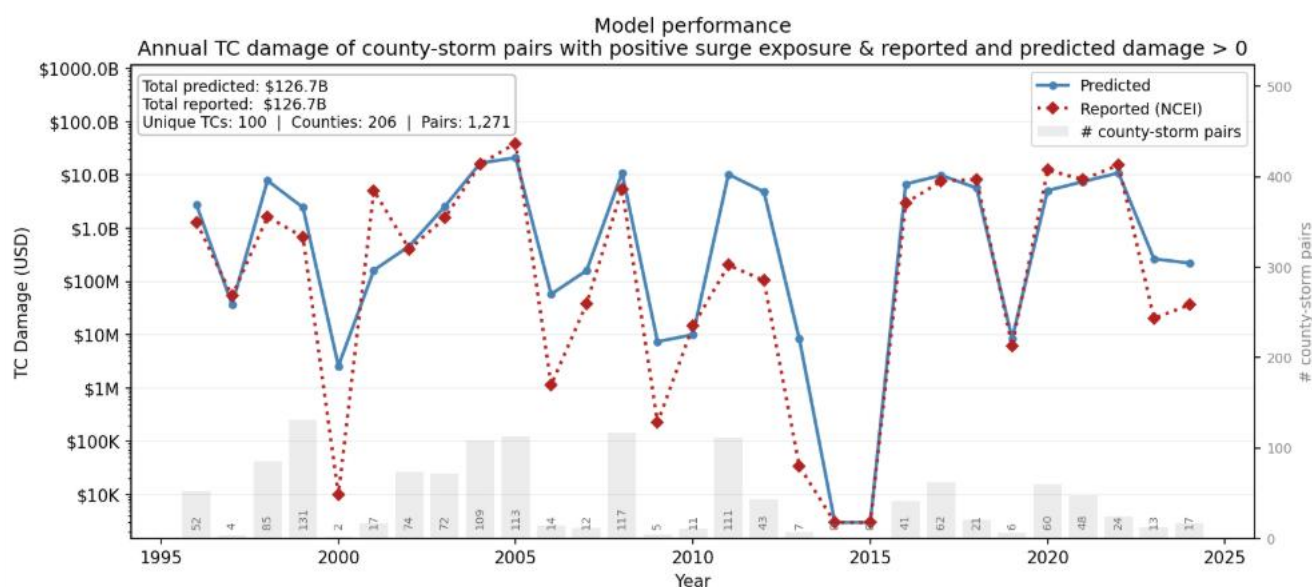


Figure 7: Annual aggregate TC damage for the model training subset (100 TCs, 206 counties, 1,271 county-cyclone pairs), comprising county-cyclone pairs with storm surge exposure, as well as positive values of reported and predicted damage. The blue line shows predicted damage; the red dashed line shows reported damage from the NCEI Storm Events Database¹⁸. The y-axis is logarithmic; years without qualifying pairs are plotted at a floor value below the data range. Grey bars (right axis) indicate the number of qualifying county-cyclone pairs per year. Total predicted and total reported damage each equal USD 126.7 bn over the full evaluation period.

Exposure Mapping

²⁴ Silva, J. M. C. S., & Tenreyro, S. (2006). The Log of Gravity. *The Review of Economics and Statistics*, 88(4), 641–658.

The COMPASS exposure datasets²⁵ provide gridded net fixed asset values at 30 arcsecond spatial resolution and annual temporal resolution. Using year-specific asset values ensures that the exposure weighting in the calculation of hazard indicators (see Section 2.4.1) reflects the capital stock at the time of each event.

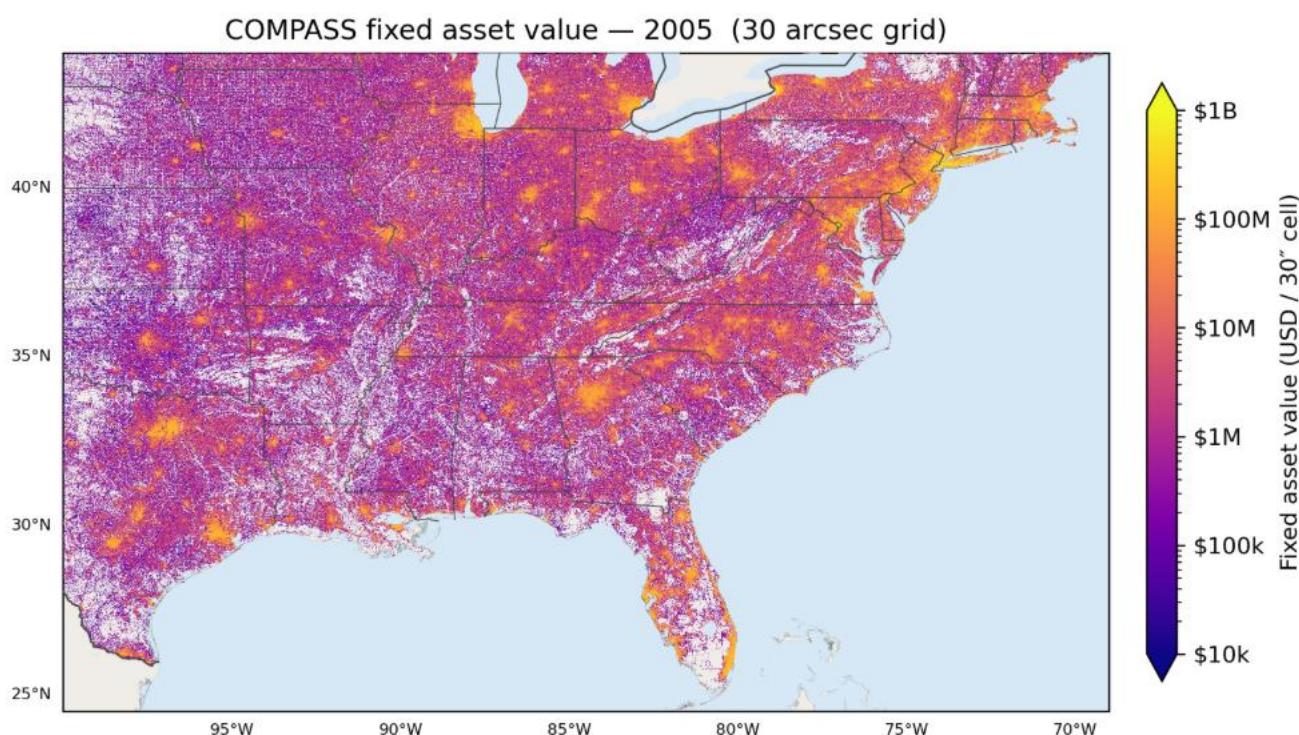


Figure 8: Exemplary exposure of fixed asset value for the year 2005 at 30 arcsecond resolution, used to calculate county-level asset-weighted hazard intensity sums for wind, rainfall and storm surge (see Section 2.4.1). The data is computed customly based on the published code of the COMPASS exposure datasets²⁵. Values are expressed in 2017 US dollars at purchasing power parity.

Vulnerability Modelling

The vulnerability to the different hazards is expressed implicitly through the calibrated coefficients β_1 , β_2 and β_3 of the impact model (see Section 2.4.2).

2.5. Attribution modeling framework

2.5.1. Event definition

We define an event as a county-cyclone pair, which represents the occurrence of damage in county x from tropical cyclone y . The attribution exercise covers a total of 5,034 county-cyclone pairs from 104 TCs between 1996 and 2024, affecting 224 counties.

2.5.2. Factual and counterfactual simulations

First, we simulate factual damages per county and tropical cyclone based on factual predictors for each county-cyclone pair and the calibrated damage model (see Section 2.4.2). Then, we calculate counterfactual damages for the same set of county-cyclone pairs, using counterfactual hazard predictors for storm surge, while keeping wind and rainfall indicators constant. The counterfactual predictors are computed using counterfactual storm surge data from Mengel¹⁵. This data set includes counterfactual data for a no sea level rise scenario (no-SLR),

²⁵ Paprotny, D. (2025). *Exposure datasets at multiple scales* (Version v2) [Dataset]. Zenodo. <https://doi.org/10.5281/ZENODO.17572467>

which was derived by removing the long-term sea level rise from the water level inputs²⁶. In addition, it provides a 1-meter sea level rise scenario (1m-SLR). We use the former for the main attribution exercise of this use case but also calculate damages for the latter to serve as a reference point (see Section 2.6.2). We do not assess individual county-cyclone damages, nor county-level aggregates, but only aggregate damages on the annual level.

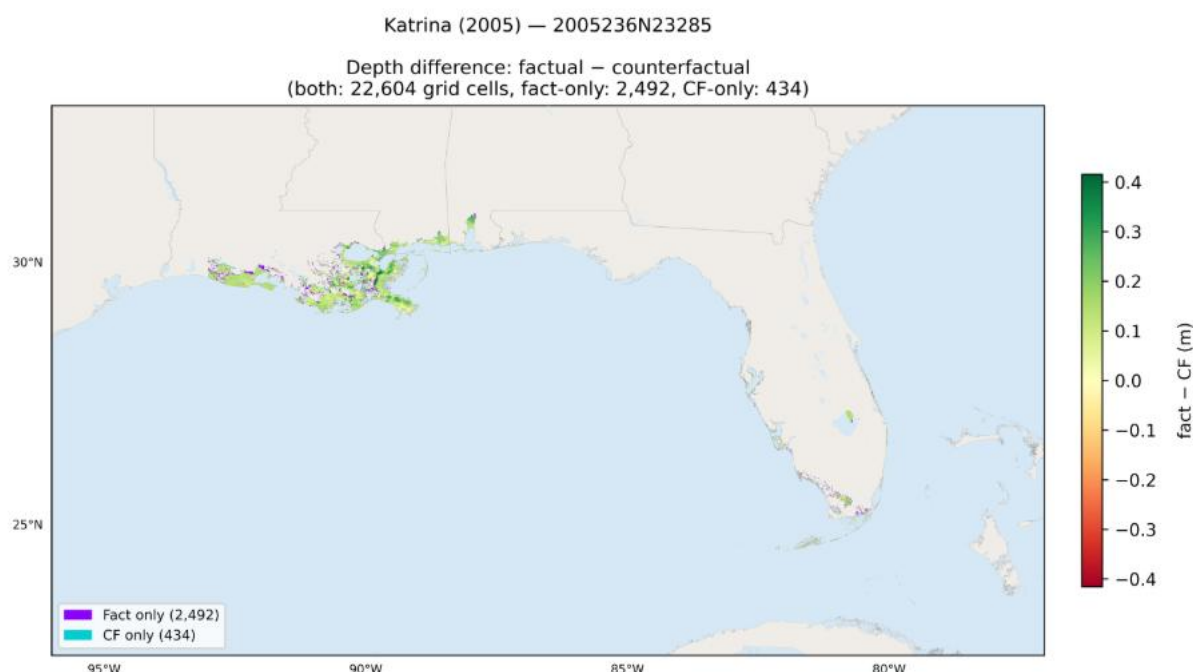


Figure 9: Exemplary inundation difference of Hurricane Katrina, calculated by subtracting factual from counterfactual (no-SLR) inundation depths. Both factual and counterfactual inundation data are provided by Mengel et al.^{15,16,22}, modelled on a 30 arcsec grid using the geophysical flow solver GeoClaw¹⁷. Factual storm surge footprints and fact-CF difference maps for all other assessed tropical cyclones can be found at https://www.pik-potsdam.de/~janhasel/compass_d4.2/surge_maps/.

2.6. Results

Tropical cyclones already cause significant damage in the United States, and climate change is likely to worsen the situation. Although the total number of tropical cyclones may decline slightly, the share of intense tropical cyclones is expected to increase. In addition, rising sea levels and heavier rain are expected to increase both coastal and inland flooding^{7,8}. Combined with continued population and economic growth along the coast, this points toward substantially higher damage in the absence of further adaptation^{10,11}. The magnitude of damages is already a problem today: FEMA's Disaster Relief Fund has faced fiscal difficulties multiple times, mainly due to clusters of extreme TCs like Katrina, Rita, and Wilma in 2005, and Harvey, Irma, and Maria in 2017, as well as unemployment insurance during the COVID-19 pandemic²⁷. Despite the growing risk, it remains unclear how much of the damage from past tropical cyclones can be attributed to sea level rise, as opposed to other factors like coastal development. In this use case, we quantify sea level rise-induced damages on coastal counties in the

²⁶ Treu, S., Muis, S., Dangendorf, S., Wahl, T., Oelsmann, J., Heinicke, S., Frieler, K., & Mengel, M. (2024). *Reconstruction of hourly coastal water levels and counterfactuals without sea level rise for impact attribution*. Earth System Science Data, 16(2), 1121–1136. <https://doi.org/10.5194/essd-16-1121-2024>

²⁷ Horzempa, R. (2018). *Drowning in Debt: The Economic Failures of the National Flood Insurance Program and Why It Will Never Rise above Water*. Review of Banking and Financial Law, 38, 391.

United States between 1996 and 2024. We do so by comparing factual simulated damages with counterfactual simulated damages that were derived from counterfactual storm surge data without SLR.

2.6.1. Factual hazards and impacts

While we do not make use of reported hazard data, we simulate factual hazard footprints based on IBTrACS⁴ track data. Table 2 shows that the assessed tropical cyclones cover a wide range of intensities, which is also visible in the plots of the individual hazard footprints (Supplementary Plot Viewer at https://www.pik-potsdam.de/~janhasel/compass_d4.2/). While the reported damage data used for the calibration of the damage model is not complete, meaning that annual/national totals may be incomplete, it still gives some insights into the magnitude of damages on the county-level. The training dataset includes a total of 1,271 county-cyclone observations from 100 tropical cyclones between 1996 and 2024, affecting a total of 206 counties. Total reported damages amount to USD 126.7 bn, with mean damage of USD 99.7 M and median damage of USD 500 k (nominal values).

In the factual simulation of damages, which includes county-cyclone pairs which no reported damages were available for, a total of 5,034 county-cyclone events from 104 tropical cyclones between 1996 and 2024 were considered, affecting a total of 224 counties. Total simulated damages amount to USD 177.0 bn.

2.6.2. Attribution results

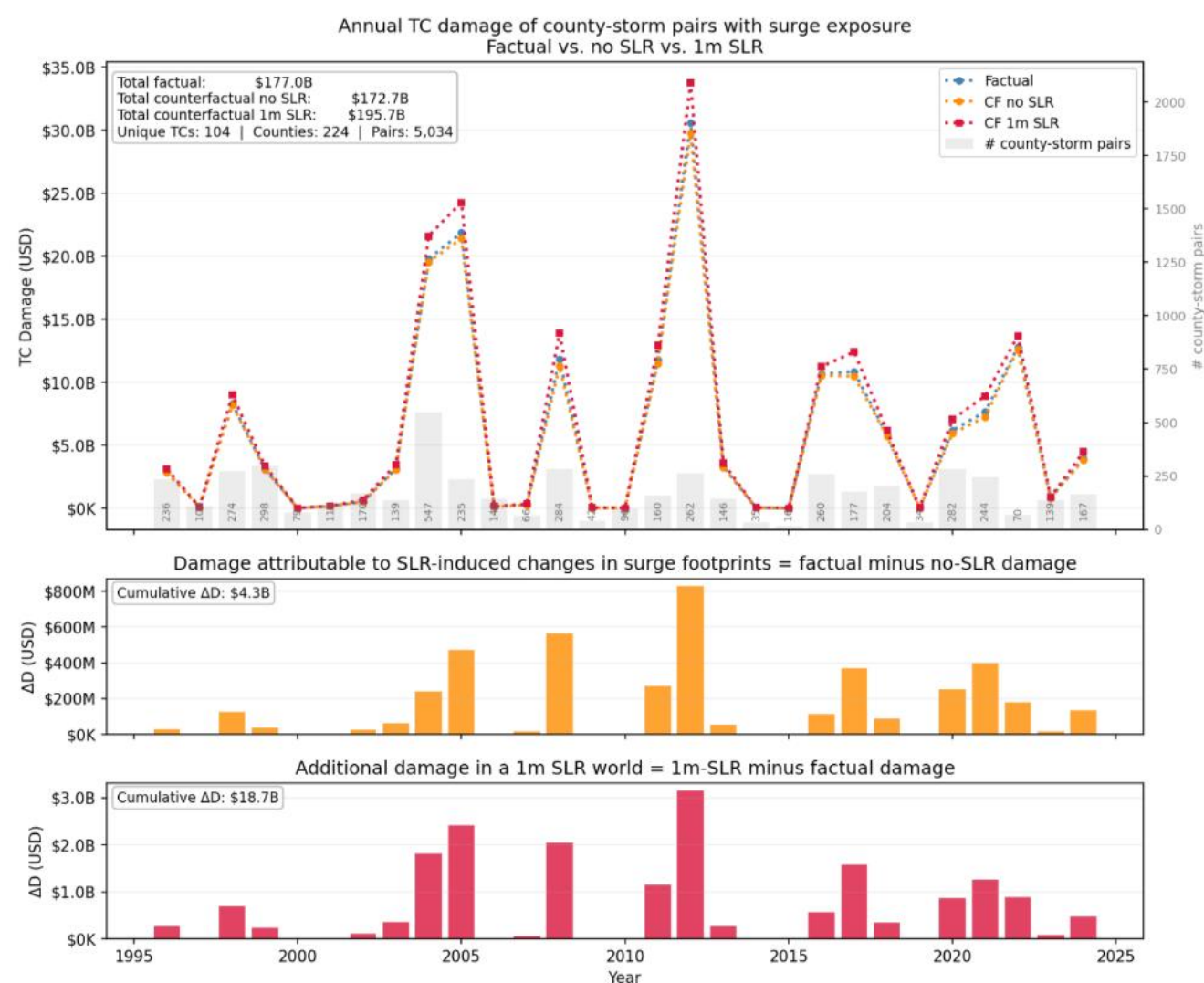


Figure 10: Annual aggregate TC damage for county-cyclone pairs with storm surge exposure (104 TCs, 224 counties, 5,034 pairs; 1996–2024), simulated using different sea-level rise (SLR) scenarios. Top panel: blue line — factual predictions based on storm surge heights which include SLR; orange line — counterfactual predictions with historical SLR removed from storm surge (no-SLR); red line — counterfactual predictions with constant 1m sea-level rise compared to no-SLR scenario (1m-SLR). Grey bars (right axis) indicate the number of county-cyclone pairs per year. Middle panel: annual damage attributable to SLR (ΔD = factual – counterfactual no SLR). The cumulative SLR-attributable damage over the study period is USD 4.3 bn, amounting to approximately 2.4% of total factual simulated damage (USD 177.0 bn). Lower panel: additional annual damage in the 1m SLR scenario compared to the factual scenario (ΔD = counterfactual 1m SLR – factual). The cumulative additional damage over the study period is USD 18.7 bn, amounting to approximately 10.6% in additional damage compared to the factual simulated damage (USD 177.0 bn). All values are in nominal USD.

We derive the attribution results by comparing simulated damages of the factual scenario with simulated damages from the no-SLR scenario. We do so based on annual totals and cumulative totals but also highlight individual tropical cyclones, which exhibit large attributable damages (see Table 4).

Our findings indicate that sea level rise has moderately increased asset damage. Over the study period 1996–2024, the fraction of attributable damage to SLR (FAD), defined as the difference between modeled factual and counterfactual total damage relative to modeled total damage (Fig. 10), amounts to FAD=2.4% or \$4.3B.

This fraction varies across tropical cyclones. Storms with reportedly large surge contribution to damage consistently have higher than average FADs (Table 4). For instance, Hurricane Gustav (FAD=6.0%) caused large coastal floodings across the Northern Gulf Coast. The Mississippi Delta region southeast of New Orleans experienced some of the worst surge flooding, with reported surges of 12–13 feet. Other southeastern Louisiana coastal areas saw 2.5 to 3m surges; Hurricanes Rita (FAD=5.3) and Ida (FAD=5.4%), which produced extreme storm surges in parts of coastal Louisiana, in 2005 and 2021, respectively. One notable exception is Hurricane Katrina; though known for its exceptionally large storm surge damage, it has a somewhat below average FAD of 2.1%. The reason could be that, for some regions, our modeling does not adequately capture the storm surge and the levees.

As a reference, we also calculate damages arising in the 1m-SLR counterfactual scenario (note that the 1m-SLR relates to 1m sea-level rise compared to the no-SLR scenario) and compare them with the factual damages. Results show additional cumulative damages of USD 18.7 bn over the study period, or 10.6% of factual simulated damages).

Table 4: Top 15 TCs by total factual damage in storm surge-affected counties and their corresponding counterfactual damage (w/o SLR). Fractional attributed SLR damages range from 0.5 to 6.0%. USD values are nominal values.

TC	Pred. factual (USD bn)	Pred. w/o SLR (USD bn)	SLR attribution (USD bn)	SLR attribution (%)
Gustav (2008)	5.41	5.09	0.32	6.0%
Ida (2021)	7.44	7.04	0.40	5.3%
Rita (2005)	3.83	3.63	0.20	5.3%
Ike (2008)	5.33	5.10	0.22	4.2%
Isaac (2012)	4.86	4.66	0.20	4.1%

Irma (2017)	8.70	8.38	0.32	3.7%
Sandy (2012)	25.70	24.99	0.71	2.8%
Irene (2011)	11.74	11.46	0.28	2.4%
Katrina (2005)	8.93	8.74	0.19	2.1%
Jeanne (2004)	5.69	5.58	0.10	1.8%
Ian (2022)	11.09	10.94	0.16	1.4%
Georges (1998)	5.76	5.70	0.06	1.1%
Matthew (2016)	10.26	10.15	0.10	1.0%
Wilma (2005)	7.14	7.07	0.07	1.0%
Frances (2004)	6.73	6.69	0.03	0.5%

2.6.3. Stakeholder and policy relevance

In recent years, the financing of coastal flood risk in the United States has come under increasing pressure. In many coastal states, private insurers have substantially increased premiums, reduced coverage, or withdrawn from particularly high-risk markets, making insurance less affordable and, in some locations, less accessible^{28,29}. At the same time, public disaster assistance has faced growing fiscal pressure. FEMA's Disaster Relief Fund has repeatedly required supplemental appropriations following major disasters, including the 2005 tropical cyclone season (Katrina, Rita, and Wilma) and the 2017 season (Harvey, Irma, and Maria), highlighting the increasing financial burden of disaster recovery²⁷.

Our results indicate that anthropogenic sea-level rise has already contributed to this challenge over the past decade by increasing tropical cyclone flood damages. While the attributable increase in damages remains small compared with FEMA's average annual expenditures, our simulations under an additional 1 meter of SLR suggest that these costs could increase substantially in the future. These findings underscore the importance of combining mitigation with forward-looking adaptation measures, including investments in coastal protection, risk-informed land-use planning, and financially sustainable insurance and disaster recovery mechanisms, to maintain the affordability and availability of flood risk financing under continued climate change.

By quantifying the fraction of present-day damages attributable to sea-level rise, attribution studies can help governments and insurers anticipate future financing needs, evaluate the long-term sustainability of disaster recovery systems, and inform adaptation and risk-transfer strategies before increasing sea levels place existing insurance and public compensation mechanisms under greater strain.

²⁸ Badger, E., & Washington, J. (2025, November 19). A climate “shock” is eroding some home values. New data shows how much. The New York Times. <https://www.nytimes.com/interactive/2025/11/19/climate/home-insurance-costs-real-estate-market.html>

²⁹ Flavelle, C., & Rojanasakul, M. (2024, December 18). Insurers are deserting homeowners as climate shocks worsen. The New York Times. <https://www.nytimes.com/interactive/2024/12/18/climate/insurance-non-renewal-climate-crisis.html>

3. Use case 2a: United Kingdom winter storms (2013/2014) extended

3.1. Summary of findings phase 1

From December 2013 to February 2014, the UK was hit by a succession of powerful winter storms which brought widespread flooding and damages totaling £1.3 billion³⁰. The low-lying Somerset Levels in southwest England were particularly affected, for example they contained 30% of the UK's flooded agricultural land. Many communities were cut off due to flood-related road closures, and there were significant power outages and mental health impacts alongside economic challenges due to flooded businesses and reduced tourism. The storms also brought strong winds – gusting at 62kn or higher in Somerset – as well as storm surges and large waves which coincided with particularly high spring tides, resulting in overtopping of coastal defenses. The total winter rainfall in Somerset was 536.6mm, which is almost double the 1991-2020 long term average of 284.8mm.

The SFINCS (Super-Fast Inundation of Coasts) compound flood model³¹ was used to simulate the flood extent under observed atmospheric conditions. SFINCS is preceded by the wflow hydrological model with input of auxiliary meteorological variables from the ERA5 global reanalysis³². The factual event was simulated using the CEH-GEAR1hr³³ precipitation dataset as input and validated against the observed flood extent, and a smaller region of the Somerset Levels that validated best was later selected for the attribution analysis. 300 further factual simulations were run using the HadGEM3-A large ensemble attribution runs³⁴, with the input precipitation validated and bias-corrected against Had-UK gridded observations over 1961-2010, alongside 300 counterfactual simulations. These large ensembles are conditioned on monthly sea surface temperatures and sea ice concentrations, which are perturbed to pre-industrial levels for the counterfactual ensemble.

The winter 2013/14 flood extent was found to have been made 1.21 times more likely, albeit with large uncertainties, under anthropogenic climate change, with the factual return period being 206.43 years, and the counterfactual 248.90 years³⁵. Furthermore, a flood event under counterfactual (natural) forcing with the factual return period would be slightly less severe in extent, at 113.4 km² instead of 114.02 km². Neither result was statistically significant. The increase in population in the area since 1870, and thus exposed to the flood event, was noted, although overall the Somerset Levels are very sparsely populated and the main impacts were on agriculture and transport.

³⁰ Environment Agency, 2016. https://rpaltd.co.uk/uploads/report_files/the-costs-and-impacts-of-the-winter-2013-to-2014-floods-report.pdf

³¹ SFINCS: Super-Fast Inundation of Coasts model. <https://doi.org/10.5281/zenodo.10118583>

³² Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., Nicolas, J., Peubey, C., Radu, R., Schepers, D., Simmons, A., Soci, C., Abdalla, S., Abellan, X., Balsamo, G., Bechtold, P., Biavati, G., Bidlot, J., Bonavita, M., De Chiara, G., Dahlgren, P., Dee, D., Diamantakis, M., Dragani, R., Flemming, J., Forbes, R., Fuentes, M., Geer, A., Haimberger, L., Healy, S., Hogan, R. J., Hólm, E., Janisková, M., Keeley, S., Laloyaux, P., Lopez, P., Lupu, C., Radnoti, G., de Rosnay, P., Rozum, I., Vamborg, F., Villaume, S., and Thépaut, J.-N. (2020). *The ERA5 global reanalysis*. Q. J. Roy. Meteor. Soc., 146, 1999–2049, <https://doi.org/10.1002/qj.3803>

³³ Lewis, E. et al., (2022). *Gridded estimates of hourly areal rainfall for Great Britain 1990-2016 [CEH-GEAR1hr] v2*. NERC EDS Environmental Information Data Centre. <https://doi.org/10.5285/fc9423d6-3d54-467f-bb2b-fc7357a3941f>

³⁴ Ciavarella, A., Christidis, N., Andrews, M., Groenendijk, M., Rostron, J., Elkington, M., Burke, C., Lott, F. C., & Stott, P. A. (2018). *Upgrade of the HadGEM3-A based attribution system to high resolution and a new validation framework for probabilistic event attribution*. Weather and Climate Extremes, 20, 9-32. <https://doi.org/10.1016/j.wace.2018.03.003>

³⁵ Jack, C. (2025). *Hazard and Impact Synthesis and Attribution for Phase I use case*. Zenodo. <https://doi.org/10.5281/zenodo.17099072>

3.2. Objective of extension

In phase I the HadGEM3-A simulations were used to create a large ensemble of winter flood extents in both factual and counterfactual (pre-industrial) forcings, which enabled a probabilistic investigation of the likelihood of the observed flood extent being reached. The primary objective of this extension was to investigate an alternative, storyline-based approach to attribution. This enabled the use of UKCP18 Local Projections³⁶ as an alternative to HadGEM3-A, using different time slices as indication of precipitation levels under different climate forcings, while preserving the timeseries of sequential storms in the 2013/14 winter that compounded the flooding. UKCP Local is a 2.2km resolution, convection-permitting model (CPM), so should provide a more accurate representation of precipitation than the coarser 60km resolution of HadGEM3-A, where convection is parametrized. This approach also enabled the creation of a counterfactual in a warmer “3°C world” using projections of the future climate. As UKCP Local projections begin in 1980, a more recent baseline of 1980-2000 was used, as opposed to the pre-industrial baseline of HadGEM3-A.

3.3. Updated (attribution) modeling framework

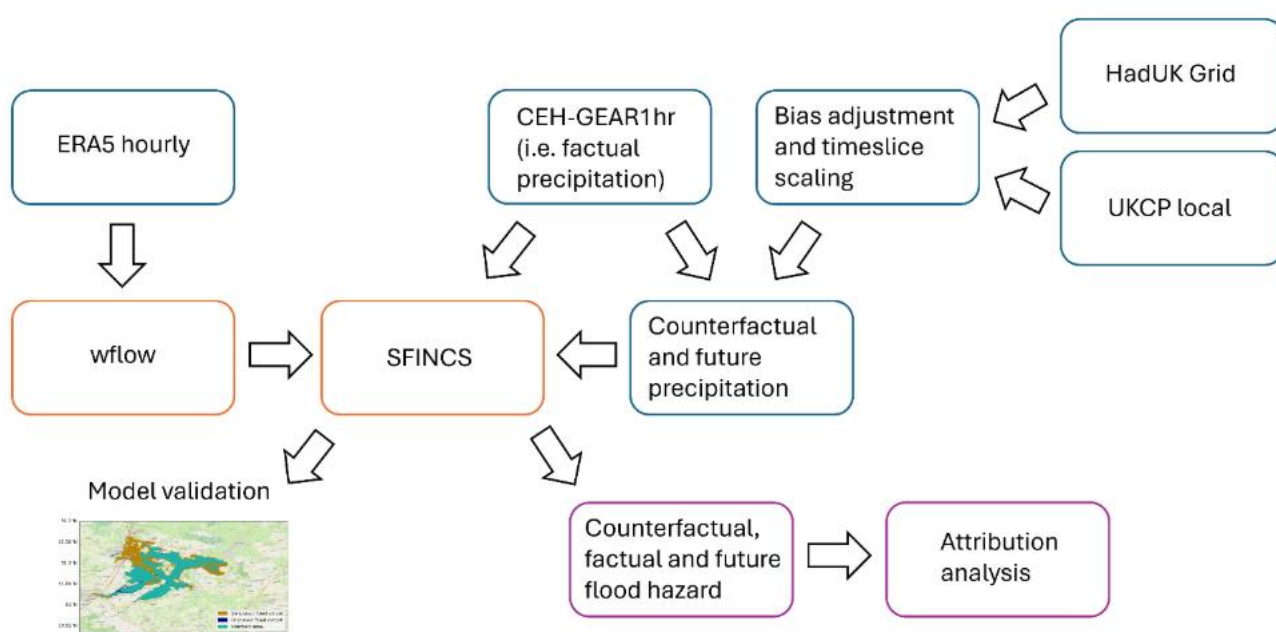


Figure 11: Flowchart of hazard and attribution modelling framework. CEH-GEAR1hr and HadUK Grid are observed precipitation datasets, wflow is the hydrological model, SFINCS is the compound flood model.

3.3.1. Updated factual simulation

As in phase 1, we use the wflow + SFINCS compound flood modelling chain to simulate the event. However, an alternative model configuration was used, using new versions of the models. The SFINCS model resolution was 100m² as opposed to 90m² used in phase 1, and a different, coarser digital elevation model (FABDEM³⁷, Forest and Buildings removed Copernicus 30m DEM) was used. However, the factual simulation was forced with the

³⁶ Kendon, E., Short, C., Pope, J., Chan, S., Wilkinson, J., Tucker, S., Bett, P., and Harris, G. (2021). *Update to UKCP local (2.2km) projections*. https://www.metoffice.gov.uk/pub/data/weather/uk/ukcp18/science-reports/ukcp18_local_update_report_2021.pdf

³⁷ Hawker, L., Uhe, P., Paulo, L., Sosa, J., Savage, J., Sampson, C., & Neal, J. (2022). *A 30 m global map of elevation with forests and buildings removed*. *Environmental Research Letters*, 17(2), 024016.

same input data as in phase 1, from ERA5 and CEH-GEAR. As in phase 1, no explicit coastal or river defenses were included.

3.3.2. Counterfactual simulations

Climate-counterfactuals

The CEH-GEAR 1-hourly observed precipitation estimates, used as the precipitation forcing for the factual flood model simulation, were also scaled to create counterfactual forcings. To do this, an alternative factual timeseries of precipitation was firstly produced using HadUK-Grid³⁸. This is a gridded observational dataset produced at a range of resolutions; we used the 5km resolution grid. We shift this alternative observation data to be within the distribution of UKCP Local, which is a set of downscaled, convection permitting climate projections produced as part of UKCP18. Here, we used the 2.2km resolution grid; the projections at this resolution exclusively use the high emissions RCP8.5 scenario. This meant we had a timeseries of the 2013/14 winter precipitation for which scaling factors to other UKCP timeslices could be calculated.

The daily precipitation values for the winter (DJF) of 2013/14 were used for this bias adjustment of HadUK. For each dataset, daily values were calculated by regridding the daily winter precipitation values onto an ERA5 grid and averaging over the two grid cells in the Somerset Levels region. The time periods used were 1970-2020 for HadUK and 1980-2010 for UKCP Local, with all 12 ensemble members of the latter used, giving a total of 360 winters to compare to HadUK. Subsequently, a gamma distribution was fitted to the resulting HadUK daily values and another to the UKCP Local daily values. Bias adjustment was applied by calculating a return period for each day of winter 2013/14 in the HadUK distribution and finding the value with the equivalent return period in the UKCP local distribution.

To produce a counterfactual, UKCP Local precipitation data was investigated for two 20-year time periods: a baseline (1980-2000) for the counterfactual called timeslice 1, and a period centred on the event (2003-2023) for the factual, called timeslice 2. All 12 ensemble members were used, giving a total of 240 winters for each timeslice. These were processed into daily values over the Somerset Levels, similarly to the HadUK and UKCP Local data as described above. Gamma distributions were individually fitted to each of the timeslices, and return periods calculated for each daily value in the bias adjusted HadUK timeseries as described above, using the distribution of UKCP timeslice 2. The equivalent daily precipitation value for that return period in the UKCP timeslice 1 distribution was then found. This produced a counterfactual equivalent of the bias-adjusted HadUK timeseries, representative of the baseline period. Dividing the daily values of the counterfactual by the value for the same day of the factual produced daily values for a downlift scaling. The hourly values of observed precipitation in CEH-GEAR were then multiplied by the downlift for the associated day to produce an hourly counterfactual timeseries that could be used as input for the model.

A counterfactual that is representative of a 3°C world was also produced. We used an estimate from the literature³⁹ of 2064 as a 3°C world under RCP8.5 in UKCP18. The process used to produce the counterfactual for timeslice 1 was repeated for the time period of 2054-2074, called timeslice 3, to produce daily values for an uplift scaling. These were then applied to the observed precipitation to produce an hourly counterfactual timeseries for the 3°C world.

Figure 12 shows the daily precipitation over the Somerset Region during the Winter of 2013/14 for each scenario after the uplifts/downlifts have been applied to the CEH-GEAR dataset. This shows an increase in precipitation

³⁸ Hollis, D., McCarthy, M., Kendon, M., Legg, T., Simpson, I. (2019). *HadUK-Grid—A new UK dataset of gridded climate observations*. *Geosci Data J.* 6: 151–159. <https://doi.org/10.1002/gdj3.78>

³⁹ Hanlon, H.M., Bernie, D., Carigi, G., Lowe, J.A. (2021). *Future changes to high impact weather in the UK*. *Climatic Change* 166, 50, <https://doi.org/10.1007/s10584-021-03100-5>

for the observed/factual relative to the 1980-2000 counterfactual and for the 3°C world relative to the factual, consistent with UKCP Local’s trend towards warmer, wetter winters.

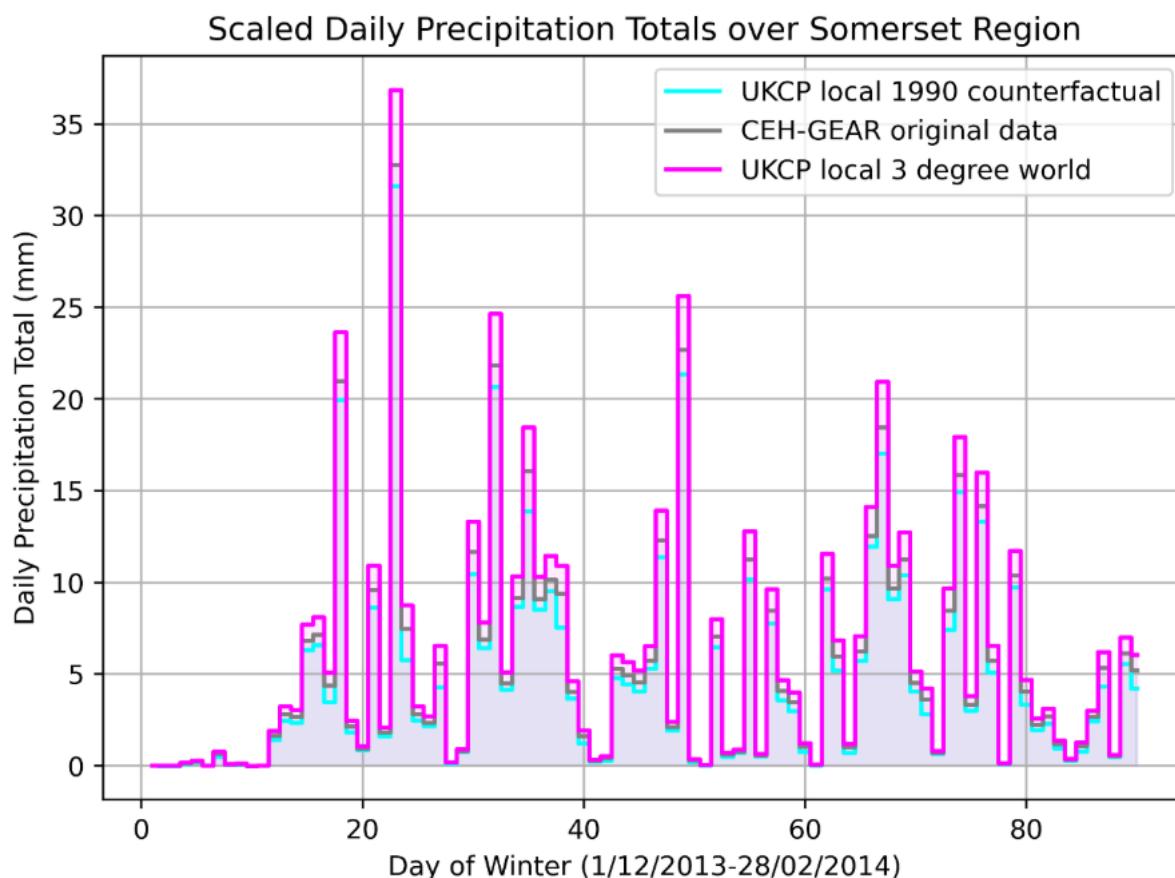


Figure 12: Daily Precipitation Total (mm) of the Somerset Region for each scenario during Winter 2013/14

3.4. Results

3.4.1. Factual and impact results

Similarly to phase 1, the simulated flood extent generated from the observed forcing, i.e. the factual climate run, was validated against observed flood extent⁴⁰. For the purposes of this analysis, we define the flooded area in the simulations as being anywhere with a flood depth greater than 0.30m. The simulation validated well, with a critical success index (CSI) of 0.63, compared to 0.64 for the validation run in phase 1.

A smaller area of the full simulated region was selected for attribution analysis which is very similar in its extent to that used in phase 1, given that this area experienced some of the more severe flooding impacts, and validated well against observed flood extent. In Figure 13 we see that nearly all of the observed flood area in this sub-region is captured in the simulation. However, the simulation shows substantially more flooding, particularly in the vicinity of Bridgwater in the north-west of the assessed region. This shows an increase in flood extent relative to the simulation used for validation in phase 1, with a reduction in flood area that was observed but not simulated, but a larger increase in the area that was simulated but not observed. This suggests that more

⁴⁰ Environment Agency (2026). <https://www.data.gov.uk/dataset/16e32c53-35a6-4d54-a111-ca09031eaaaf/recorded-flood-outlines1>

accurate results could be obtained by making adjustments to the model configuration, such as increasing resolution and using a higher resolution digital elevation model which better reflects the built environment around Bridgwater. As Bridgwater is the most urban part of the region, we would expect to find a significant overestimation of the number of people exposed to flooding in any impact assessment using this simulation.

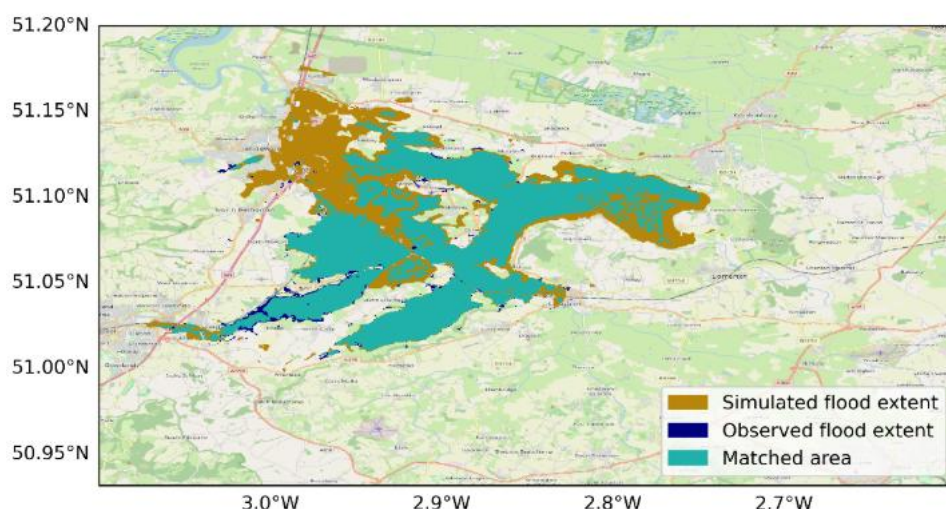


Figure 13: Validation map of simulated flood extent in factual scenario overlayed with the actual observed flood extent

3.4.2. Attribution results

In this attribution analysis, as in the validation step, only areas with a flood depth over 0.30m are considered. Table 5 shows the results for maximum flood extent, volume and depth in each of the three simulations run.

Table 5: Maximum flood extent, volume and depth for the three simulations.

Simulation	Maximum flood extent (km ²)	Maximum flood volume (Mm ³)	Maximum flood depth (m)
Counterfactual	131.136	297.388	5.579
Factual	132.256	303.935	5.626
Future	133.627	312.481	5.688

These results suggest a very small attributable climate signal for flood extent, volume and depth in the selected area. Figure 14a shows that climate change since 1990 can be considered to have increased the maximum flood extent of the 2013/14 winter event by 0.9%. In a 3°C warmed world, the maximum flood extent would be 1% greater than the 2013/14 event. Similarly, Figure 14b shows that climate change since 1990 can be considered to have increased the maximum flood volume of the 2013/14 winter event by 2.2%. In a 3°C warmed world, the maximum flood volume would be 2.8% greater than the 2013/14 event.

The largest differences in flood depth between simulations are in the south of the selected area, along the River Tone into Taunton (51.02°, -3.05°) and along the River Parrett into Langport (51.04°, -2.83°), which can be seen on Figure 15 and Figure 16. This indicates that the height of the rivers in these areas are sensitive to the amount of precipitation. In phase 1 of this use case it was suggested that the different levels of rainfall perhaps does not make much difference to the river flows following common spin-up from ERA5 forcing, given that the overall

changes in flood event characteristics are small between simulations, but some sensitivity of river flood depth to precipitation is indicated in this analysis.

The differences are larger between the factual and future simulations as opposed to the counterfactual and factual simulations. This can be understood given that there is more warming between the factual simulation (centred on 2013) and the future 3°C world (centred on 2064) than there is between the factual and the baseline counterfactual world (centred on 1990).

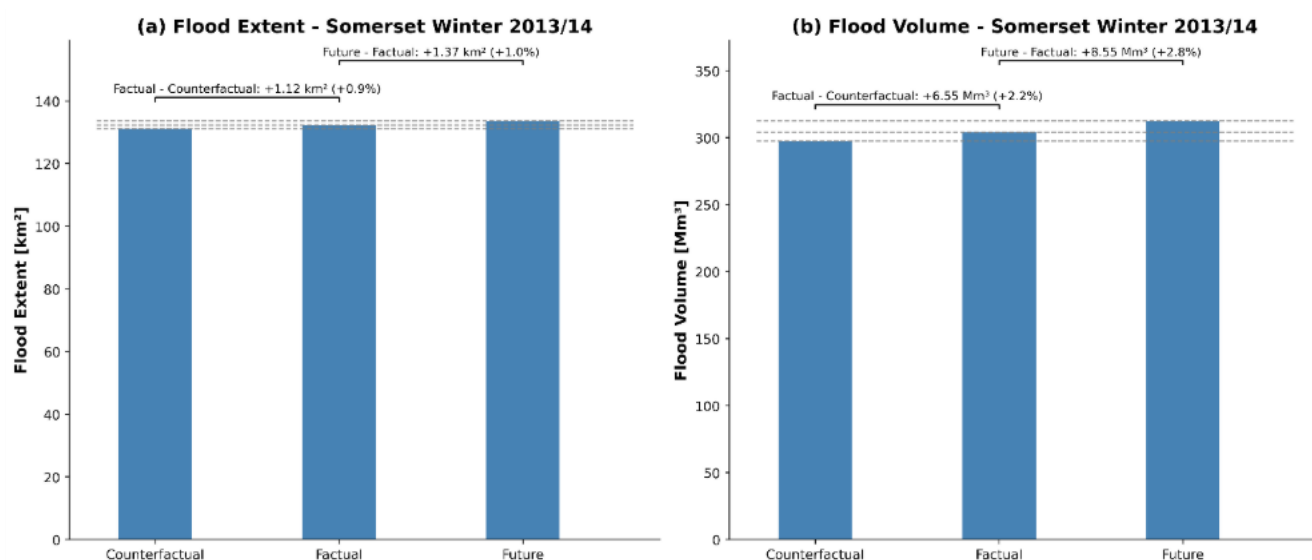


Figure 14: a) Maximum flood extent above 0.30m and b) Maximum flood volume in each of the three simulations.

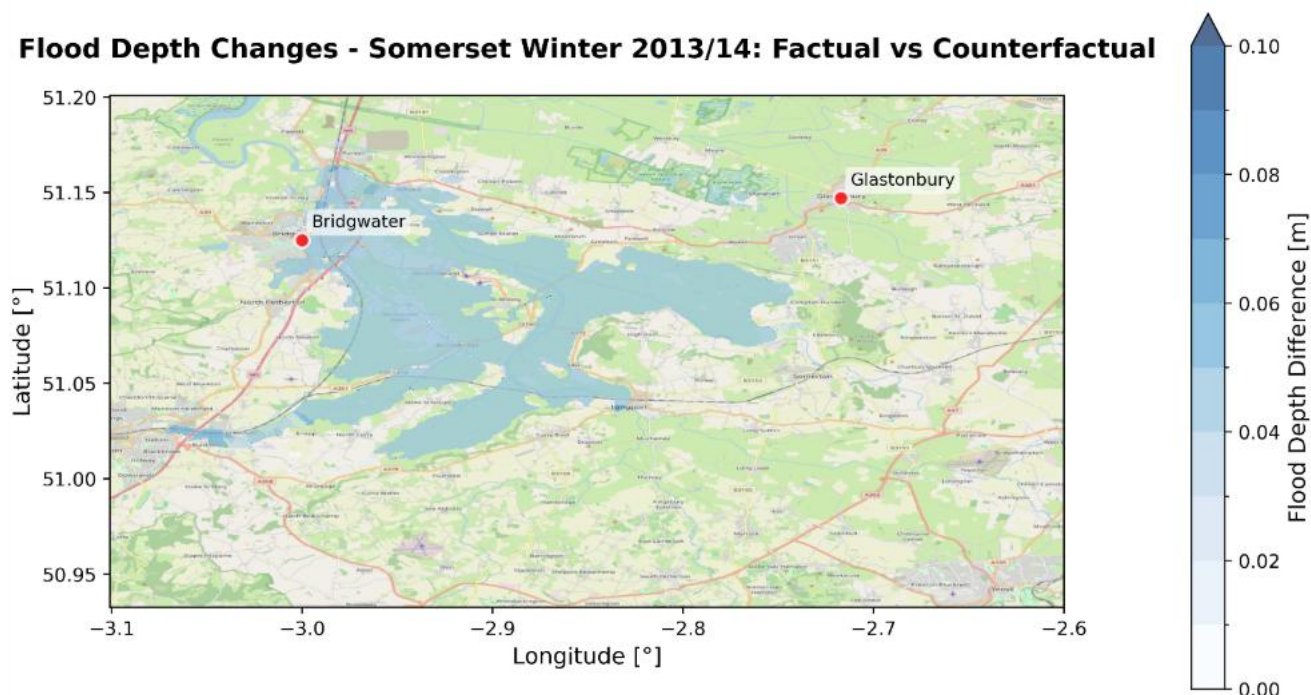


Figure 15: Map showing the difference in maximum flood depth between the factual and counterfactual simulations.

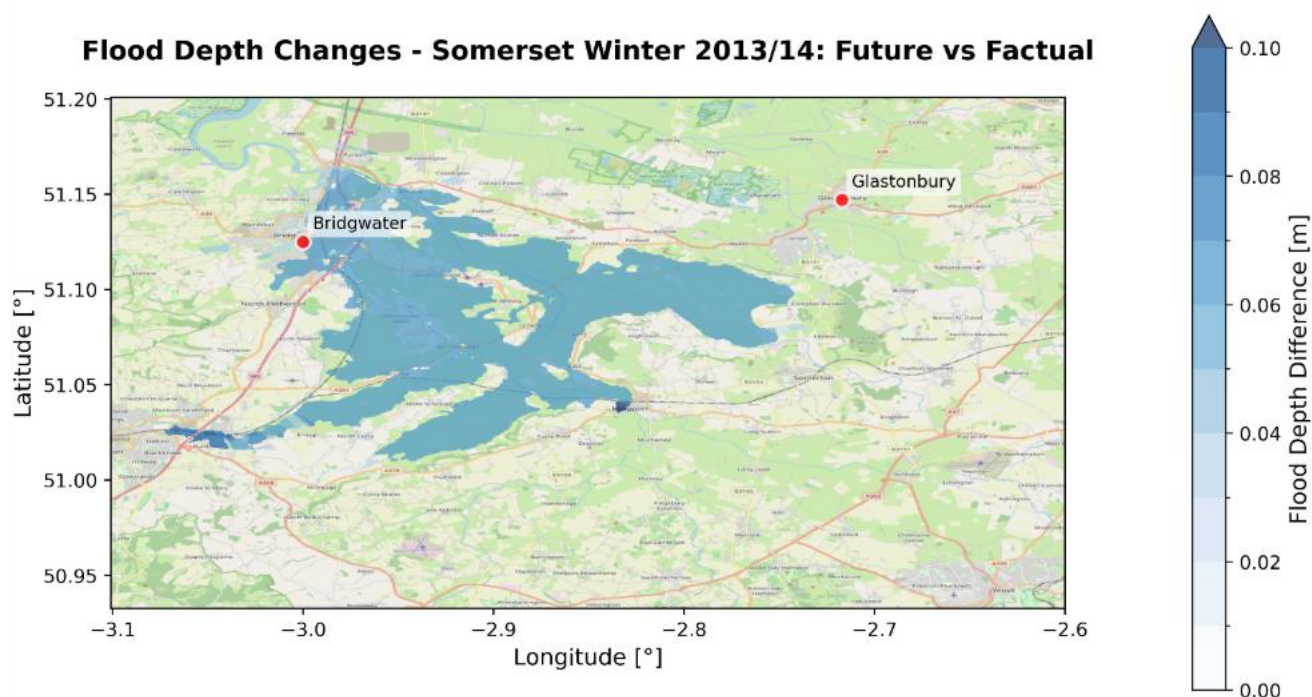


Figure 16: Map showing the difference in maximum flood depth between the future and factual simulations.

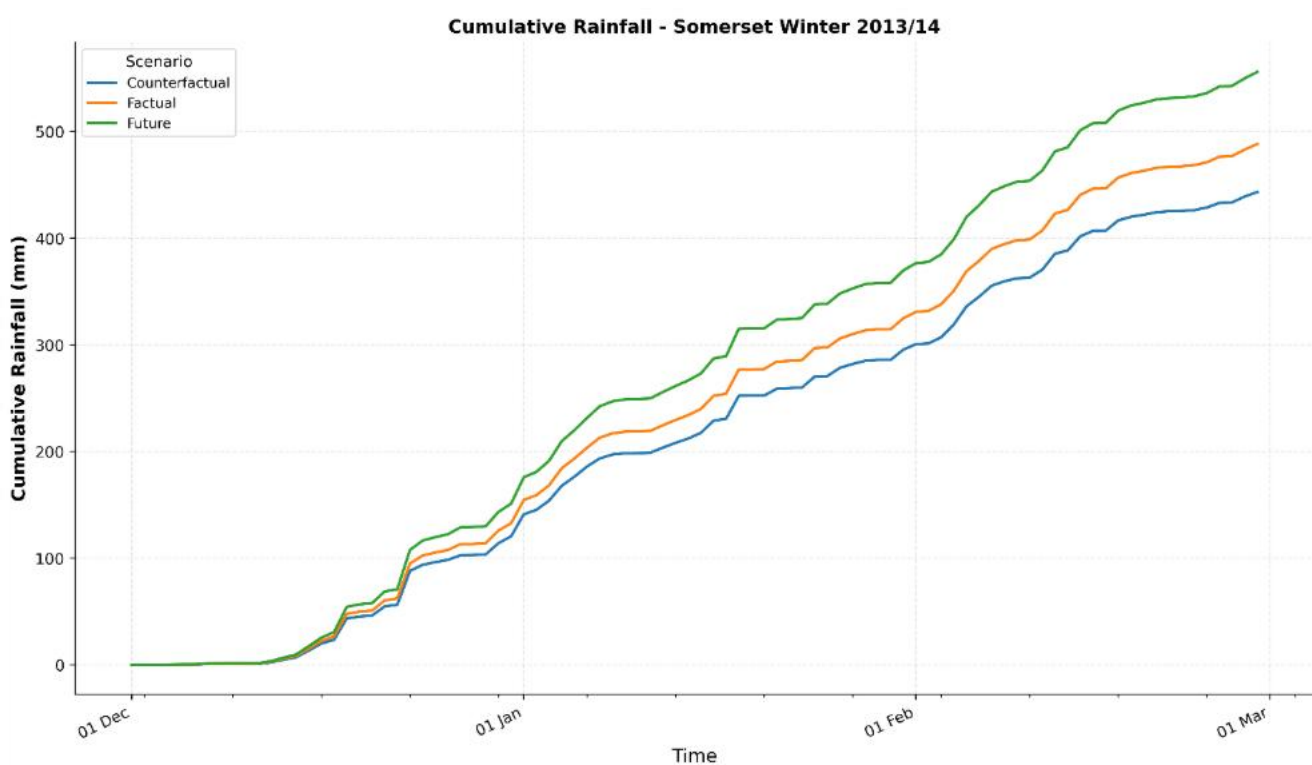


Figure 17: Cumulative rainfall (mm) by scenario for Winter 2013/14

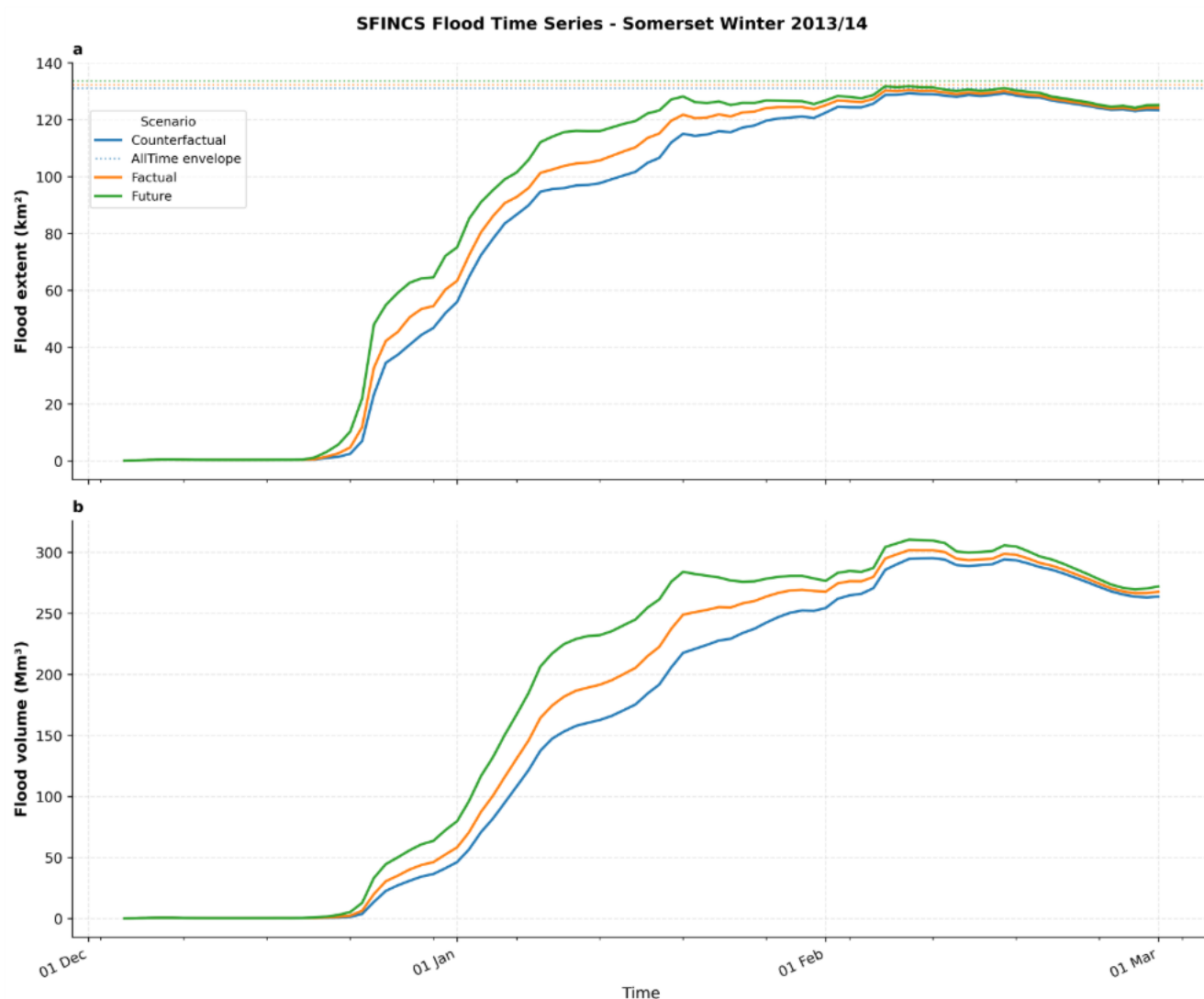


Figure 18: a) Flood extent over 0.3m and b) Flood volume over time

As well as investigating the extent, volume and depth of the maximum flooded area under different scenarios for the attribution results, investigating how the flood evolves over time alongside rainfall accumulation, as shown in Figure 17 and Figure 18, is also revealing. In mid-late December, there is a small lag between the rainfall accumulation and the flood extent and volume beginning to increase, as would be expected as rainfall travels through the flood catchment area. From mid-late December to mid-January, flood extent and volume rapidly increase, more so in the factual than counterfactual, and most rapidly in the future scenario. From late January and through February, the flood extents and volumes then begin to converge to their final values. Although rainfall kept accumulating throughout February, further rainfall did not drive greater flood extent beyond a maximum in early February, although there is a small uptick in volume at the end of February in the factual and future scenarios. Note that it is the “AllTime” envelope values from Figure 18a that are presented in Table 5 and therefore used in the attribution calculations, as these are derived from the individual maximum flood depths in each cell over the entire time series, and does not represent a specific point in time.

By visual inspection, we observe that particular upticks in rainfall accumulation can be related to sharper increases in flood extent, for example in the middle of January, which increases confidence in the flood extent accumulation as being sensitive to precipitation. This indicates the importance of the consecutive storms for driving impacts. Had the sequence of winter storms ceased earlier, for example in mid-January when the flood extents were at their most different and before the flood extent peak had been reached, then the maximum

flood extents may have settled at more disparate values. This would have resulted in a stronger climate signal being suggested. This highlights how the conditioned nature of a storyline approach means the results always need to be taken in context of the event.

There is a 10% increase in total accumulated precipitation over the 3 month period between the counterfactual and factual input data, and a 14% increase between the factual and future input data, which does not translate into the same percentage changes in flood extent or volume between scenarios, which are on the order of 1-2%, indicating there are other factors at play in controlling the flood extent in the Somerset Levels. While the maximum flood extents are used for the attribution results, the difference in the flood extent accumulation profiles reveals there to be more difference in the flooding under different scenarios than is initially apparent from the maximum values. In a world altered by climate change, i.e. the factual world, flood extent initially increases more rapidly than it would have in a counterfactual world. This means that people, land and assets are put at risk more suddenly and a quicker emergency response may be required. In a 3°C warmed world, the rate is even higher, which suggests that the Somerset region would benefit from preparing to take action more rapidly in response to flooding in future.

Comparison to phase 1 and other learnings

The probabilistic approach used in phase 1 of this use case involved running 300 simulations for each of the counterfactual and factual periods, enabling the calculation of uncertainty intervals and return periods for reaching a particular flood extent, which is not possible in this phase as we only have one simulation for each scenario. This phase focused on the conditioning of the event, preserving its spatio-temporal structure i.e. the sequence of storms that fuelled the compound flooding, so we compare “storylines” of the event under different scenarios. Running only 3 simulations rather than 600 saved significant time in this phase. In the context of a rapid operational attribution service, the storyline approach would therefore be more efficient.

The results here agree with phase 1 that only a small amount of the flooding in the 2013/14 event is attributable to climate change. However, phase 1 used a pre-industrial baseline, and found a 0.55% increase in maximum flood extent (113.4km² in the counterfactual, 114.02km² in the factual), whereas here, a larger increase of 0.9% is found since a more recent 1990 baseline. This indicates that there is a stronger climate change signal with this approach. This could be due to a combination of reasons, for example, the higher, convection-permitting resolution of the precipitation inputs used here which better captures spatial variability and climate change trends in rainfall. Although convection is a less significant process for winter storms, ongoing research demonstrates that global models such as HadGEM3 underestimate the scaling of precipitation with climate change⁴¹, and that higher resolution models are better at capturing such trends, including for autumn and early winter rainfall extremes⁴². However, the methods of each phase also answer different questions. The event conditioning on the sequence of storms in this phase, which were unusual in their temporally compounding nature, asks how the intensity change in daily rainfall totals due to climate change altered the flood extent of this event. However, phase 1, the large ensembles approach, asks whether climate change has changed the risk of high flood extent events such as that of 2013-14, due to either rainfall intensity changes or changes in the numbers of sequencing of storms. Bearing in mind the different model configurations and resolution of the input precipitation as discussed above, the differing results could therefore imply that there is a stronger climate

⁴¹ Carruthers, J. G., Fowler, H. J., Bannister, D., & Guerreiro, S. B. (2026). *Climate models tend to underestimate scaling of UK mean winter precipitation with temperature*. Geophysical Research Letters, 53(3), e2025GL118201. <https://doi.org/10.1029/2025GL118201>

⁴² Cotterill, D., Stott, P., Christidis, N., & Kendon, E. (2021). *Increase in the frequency of extreme daily precipitation in the United Kingdom in autumn*. Weather and Climate Extremes, 33, 100340. <https://doi.org/10.1016/j.wace.2021.100340>

change attribution signal for the intensity of this particular flood event having increased, as opposed to the likelihood of an event with such a flood extent occurring in the first place.

Another learning from this use case is the importance of model configuration. The slightly lower resolution used in the model for this phase (100m² compared to 90m² in phase 1) combined with a lower resolution digital elevation model (DEM) likely caused significantly more flooding over Bridgwater in this phase which did not match observations, or the flood extent results from phase 1. While the DEM used in this phase, FABDEM, is widely regarded as the best global DEM^{43,44}, and allows consistency between use cases across the globe, deciding to use such a DEM may reduce the quality of the results. Using a more local, higher resolution DEM if available, for example based on LiDAR data, is important to best represent the environment being modelled. This limits the usefulness of any impact assessment that could be produced from the results of this phase.

3.4.3. Stakeholder and policy relevance

The investigation of a flood event in a 3°C world, and potentially other global warming levels in future work, would support local government and organisations such as the Somerset Rivers Authority in making disaster preparedness and climate adaptation planning decisions for the coming decades. For example, the finding of an increased rate of flood extent build up in warmer worlds suggests that Somerset will need to be prepared to respond more rapidly to flooding in future. Such planning could build upon the 20-year action plan that was initiated in the region following the 2013/14 event, of which the 2024-34 strategy is currently underway⁴⁵. This has included contributions to the Bridgwater Tidal Barrier project (due to be completed in 2027) which is being led by the Environment Agency and Somerset Council⁴⁶.

3.5. Future work

Future work will update the model configuration, to use not only the new model versions but also use a more local DEM and increase the model resolution, and repeat the attribution analysis. This would also enable the investigation into exposed population in phase 1 to be conducted using the storyline scenarios presented here. Considering exposure and vulnerability, the use case could expand into the impact attribution space, considering the main impacts on agriculture, transport, and flooding of homes and businesses, if appropriate datasets can be identified and impact modelling chains established.

For the hazard attribution, this use case has focused on the temporal nature of the compound event, with precipitation accumulating over the winter season from the sequential storms. To consider the multivariate nature of the event and investigate attribution to sea level rise, a coastal counterfactual could also be considered, removing the sea level rise that has been observed at the Somerset coast since the baseline period of interest. To do this, the sea level could be directly modified in the time series from CODEC⁴⁷ which is used as

⁴³ Meadows, M., Jones, S., & Reinke, K. (2024). *Vertical accuracy assessment of freely available global DEMs (FABDEM, Copernicus DEM, NASADEM, AW3D30 and SRTM) in flood-prone environments*. International Journal of Digital Earth, 17(1), 2308734. <https://doi.org/10.1080/17538947.2024.2308734>

⁴⁴ Bielski, C., López-Vázquez, C., Grohmann, C. H., Guth, P. L., Hawker, L., Gesch, D., ... & Strobl, P. (2024). *Novel approach for ranking DEMs: Copernicus DEM improves one arc second open global topography*. IEEE transactions on geoscience and remote sensing, 62, 1-22. <https://doi.org/10.1109/TGRS.2024.3368015>

⁴⁵ Somerset Rivers Authority (2024). *Somerset Rivers Authority (SRA) Strategy 2024-34*. <https://www.somerset-rivers-authority.org.uk/about-somerset-rivers-authority/sra-strategy-2024-34/>

⁴⁶ Somerset Rivers Authority (2024). *Somerset Rivers Authority (SRA) Strategy 2024-34*. <https://www.somerset-rivers-authority.org.uk/about-somerset-rivers-authority/sra-strategy-2024-34/>

⁴⁷ Muis, S., Apecechea, M.I., Dullaart, J., de Lima Rego, J., Madsen, K.S., Su, J., Yan, K. and Verlaan, M. (2020). *A High-Resolution Global Dataset of Extreme Sea Levels, Tides, and Storm Surges, Including Future Projections*. Frontiers in Marine Science, 7, 263. <https://doi.org/10.3389/fmars.2020.00263>

the coastal boundary conditions for the model. Following the method used for TC Idai⁴⁸, sea level rise for the Somerset coast could be calculated from the Hourly Coastal Water Levels with Counterfactual (HCC) dataset⁴⁹. This would modify the coastal flooding component that compounds with pluvial and fluvial flooding in the model, and enable investigation of the relative contributions of each hazard to the flood extent. As well as removing the total observed sea level rise, the impact of removing only the fraction that is considered attributable to anthropogenic activity could also be investigated to separate this from sea level changes due to other factors such as vertical land motion and natural deglaciation, and thus assess the impact of anthropogenic activity on the flood extent from the coastal component. A future coastal counterfactual could also be created, and combined with the future precipitation input used in this phase, by adding projected sea level rise amounts to the coastal boundary conditions. As part of this investigation it would be important to ensure that coastal and river defenses are applied in the model configuration, to improve the accuracy of the model in representing flooding of the Somerset environment, which is particularly important when adjusting coastal inundation in the simulations. Depending on how well the model validates with these additions, a larger area could be analysed for the attribution results.

As discussed, the second phase of the use case has switched from a probabilistic approach using the HadGEM3-A large ensemble runs to a storyline approach, scaling the CEH-GEAR observation data based on bias-corrected UKCP timeslices (3.3.3). However, the probabilistic approach could also be further developed by exploiting the larger ensemble size of the more recent years of the HadGEM3-A runs, for both factual and counterfactual climates. These attribution runs each contain 15 members between 1960-2013, 105 members between 2014-2015, and 525 members between 2016-2025. In phase 1, only the 15 original ensemble members were used, with random samples of the larger ensembles for more recent years being taken to continue the timeseries, which resulted in 300 winters to simulate through the flood modelling chain in each of the factual and counterfactual climates. However, all available winters could be investigated, and those with the top 300 winter rainfall totals used for the simulations. This would model more extreme precipitation winters and improve our estimate of the return periods of certain flood extents through this method.

⁴⁸ Vertegaal, D. M., van den Hurk, B. J. J. M., Couasnon, A., Aleksandrova, N., Bovenschen, T., Gradiyanto, F., Leijnse, T. W. B., Goulart, H. M. D., and Muis, S. (2026). *Climate and impact attribution of compound flooding induced by tropical cyclone Idai in Mozambique*. Natural Hazards and Earth System Sciences, 26(3), 1417-1433. <https://doi.org/10.5194/nhess-26-1417-2026>

⁴⁹ Treu, S., Muis, S., Dangendorf, S., Wahl, T., Oelsmann, J., Heinicke, S., Frieler, K., Mengel, M. (2025). *Hourly Coastal water levels with Counterfactual (HCC)*. ISIMIP Repository. <https://doi.org/10.48364/ISIMIP.749905.1>

4. Use case 2b: United Kingdom drought heatwave (2022) extended

4.1. Summary of findings phase 1

The UK summer of 2022 was characterised by extremely hot and dry conditions leading to severe drought and five heatwave periods. Between 18th to 19th July, an unprecedented extreme heatwave affected the UK, setting new maximum temperature records across the UK and Ireland with temperatures of 40 °C recorded for the first-time. This extreme heat did not develop in isolation and in the months preceding the event, the UK, and particularly eastern and southern England, faced unusually dry and sunny conditions. These conditions acted together to create a multivariate hazard, triggering widespread, compound impacts across UK sectors.

During the peak of the heatwave, over 2000 excess heat-related deaths were recorded, transport networks were disrupted and wildfires broke out across multiple counties, alongside power cuts, school closures and agricultural losses. This use case's first stage focused on one of the most visible infrastructure failures; the melting of Luton Airport's runway on 18th July. This caused the temporary closure of the airport, leading to 13 diverted and 100 cancelled flights, disrupting thousands of passengers and putting strain on staff and airline operations.

Using linear regression, the relationship between observed air temperature and runway temperature was explored, revealing that extreme runway surface temperatures (> 45 °C) were best represented by the average 6-hourly air temperature preceding the maximum surface temperature event. This metric was used to select an impact threshold for the event within the ERA-5 land dataset, and taken forward into the attribution analysis. HadGEM3-A large-ensemble attributions runs were used to simulate the event in factual and counterfactual scenarios and were conditioned on sea surface temperatures and sea ice fields for 2022. These were validated with regrided ERA-5 land reanalysis for the grid box covering Luton Airport.

Attribution analysis revealed that the melting of Luton's runway was made 12 times more likely with anthropogenic climate change, with 95% confidence intervals showing the event was between 6 and 32 times more likely. In the current climate, this event has a return period of 14.5 years, whereas in a counterfactual climate, the event would've been incredibly rare with a return period of 175 years. The intensity of an event with the same return period (i.e. 15 years) in a counterfactual climate is 2.1 °C cooler, therefore there wouldn't have been any impacts in this scenario.

Increased usage of Luton Airport from 1980 was noted as a contributor to the severity of impacts from the melting event through increased population exposure. This combines with the airport's operational vulnerabilities, including runway material thermal tolerance and the airport's dependence on external infrastructure, to amplify the overall impact of extreme heat events, highlighting the need for targeted adaptation and resilience measures.

4.2. Objective of extension

Expansion of use case to rail network

The second phase of this use case aims to extend understanding of how the 2022 UK drought–heatwave event impacted multiple transport systems, shifting the focus from aviation to the rail network. This will highlight the spatially compounding nature of the event, showcasing how a multi-variate hazard can simultaneously impact different locations and networks across the UK.

During the peak of the heatwave, UK rail experienced significant disruption, with train cancellations, severe delays and network-wide speed restrictions. The rail period from 26th June to 23rd July recorded the highest number of delay compensation claims since the start of the COVID-19 pandemic, a likely consequence of the

drought-heatwave event⁵⁰. The most severe disruption occurred across eastern and central England, including the closure of the East Coast Main Line on 19th July and the suspension of services from northern England and the Midlands into London Euston and St Pancras International⁵¹.

Given the severity and spatial extent of these impacts, this extension is essential for understanding the contribution of climate change to this event, particularly as extreme heat and drought events become more severe, frequent and prolonged in the future. Such insights are important for informing long-term adaptation and resilience planning for the UK rail network.

Novel modelling approach and methods

This use case aims to widen the transport assessment by applying the Met Office’s operational Surface Transport Forecasting (STF) model in a novel climate attribution context. This impact model is primarily used to produce weather forecasts of road-, rail- and runway-specific diagnostics, such as surface temperature and ‘state’ e.g. dry, damp, icy, which are essential inputs for defence, government, and commercial Met Office services. This work will explore the feasibility of forcing the STF model with climate attribution datasets rather than weather data, with the aim of assessing its capability to translate climate hazards into transport impacts.

By doing this, this case study will explore the compounding influence of air temperature and solar radiation in determining heatwave intensity and resulting rail impacts. It will also use novel climate datasets, including Destination Earth storylines, to showcase evolving methods of climate attribution studies. This will allow us to trial a storyline-based approach for the same drought-heatwave event examined in the phase 1 use case, which used probabilistic methods. This will offer insight into the conclusions that can be made from different attribution methods and how they can be used to support decision-making.

4.3. Updated (attribution) modeling framework

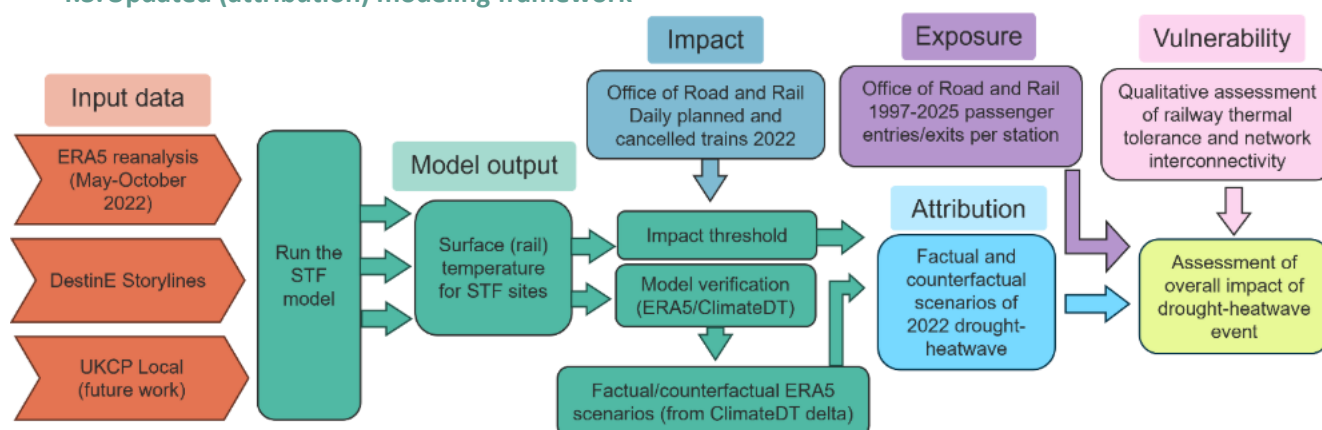


Figure 19: Flowchart of attribution modelling framework

Figure 19 summarises our attribution modelling framework. To assess the influence of anthropogenic climate change on the rail impacts of the 2022 drought-heatwave, we simulate factual and counterfactual scenarios using the Met Office Surface Transport Forecasting-JULES (STF-JULES) impact model (described in 4.3.2). The factual scenario is representative of the current climate, whereas the counterfactual represents a scenario

⁵⁰ Office of Rail and Road (2022). *Rail delay compensation claims: Rail periods 1 to 4, 1 April 2022 to 23 July 2022*. Office of Rail and Road, 27 October 2022. Available at: <https://dataportal.orr.gov.uk/media/2147/delay-compensation-claims-factsheet-2022-23-rail-periods-1-4.pdf>.

⁵¹ BBC News. (2022, July 19). *Trains cancelled and delayed after heatwave damage*. Available at: [BBC News article](#)

where the event occurred in a 1950s climate. This investigation is combined with an assessment of exposure and vulnerability to determine the overall impact of the extreme event.

4.3.1. Updated factual simulation (opt)

To explore the impact of climate change on the 2022 summer heatwaves, including the 40 °C day on July 19th, we investigated two different sources of climate data to drive the STF-JULES impact model – ClimateDT and ERA5-Land. ClimateDT is used as a climate attribution model to emulate the 2022 heatwave event, and ERA5-Land as a reanalysis to baseline our “truth” of the event and to drive the STF-JULES impact model in the baseline.

ClimateDT is a set of Destination Earth of fully coupled IFS-FESOM climate model runs, running from 2017 with the large-scale winds above 700 hPa continuously nudged towards ERA5 values and the ocean free-running from 2017 start conditions, with a 10km atmospheric resolution. The purpose of the ClimateDT models is to examine the same weather events under different climate forcings– 1950 for the “control” climate, present-day forcings from 2017, and forcings for a 2.0K warmer world for a future climate⁵². As only a single Gen 1 storyline member was available when the rail model was run, only one control and present-day member is used, although later evaluation showed the key temperature biases remained in the Gen 2 ensemble (Figure 20).

Previous verification work on the ClimateDT has focused on the 2019 summer heatwave over Paris⁵³ so our first step is to evaluate the performance of ClimateDT over England for the July 18/19th summer heatwave of 2022.

To evaluate ClimateDT, we compared daily maximum air temperature and downwards shortwave radiation against ERA5-Land for the 19th of July 2022. These variables were determined to be key inputs to the rail model via sensitivity analysis (see section 1.3.2). We also include two separate sources of gridded station observations for the daily maximum air temperature calculations – HadUK-Grid⁵⁴ and CrowdGrid⁵⁵. HadUKgrid is a gridded product produced from long-term official weather station records, and CrowdGrid is a similar product produced from crowdsourced consumer weather station data, with greater density of stations – especially in urban areas – allowing for better representation particularly in urban areas. For shortwave radiation, we lack such high-quality gridded products and only can compare to ERA5-Land reanalysis.

⁵² Doblas-Reyes, F. J., Kontkanen, J., Sandu, I., Acosta, M., Al Turjman, M. H., Alsina-Ferrer, I., Andrés-Martínez, M., Anerdi, C., Arriola, L., Axness, M., Batlle Martín, M., Bauer, P., Becker, T., Beltrán, D., et al. (2026). *The Destination Earth digital twin for climate change adaptation*. Geoscientific Model Development, 19, 2821–2864. <https://doi.org/10.5194/gmd-19-2821-2026>

⁵³ Sánchez-Benítez, A., Goessling, H., Pithan, F., Semmler, T., & Jung, T. (2022). *The July 2019 European Heat Wave in a Warmer Climate: Storyline Scenarios with a Coupled Model Using Spectral Nudging*. Journal of Climate, 35(8), 2373–2390. <https://doi.org/10.1175/JCLI-D-21-0573.1>

⁵⁴ Hollis, D., McCarthy, M., Kendon, M., Legg, T., & Simpson, I. (2019). *HadUK-Grid—A new UK dataset of gridded climate observations*. Geoscience Data Journal, 6(2), 151–159. <https://doi.org/10.1002/gdj3.78>

⁵⁵ Fry, M., Mitchell, T., Chapman, L., Pope, F., & Farrar, L. (2026). *Crowd-Grid & Recent Heat Packs: From crowdsourced observations to a prototype climate service*. EGU General Assembly 2026, EGU26-5694. <https://doi.org/10.5194/egusphere-egu26-5694>

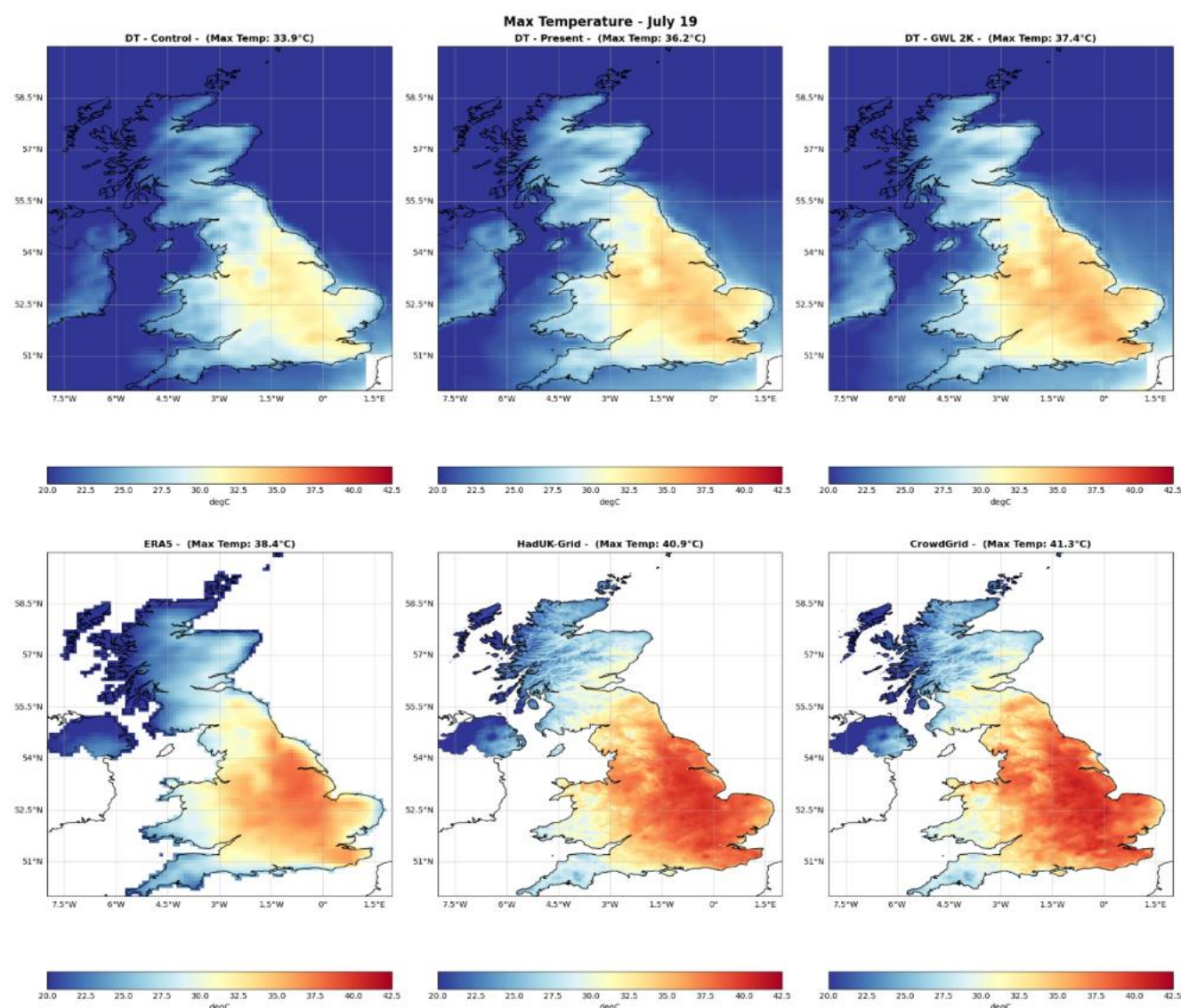


Figure 20: Maximum temperatures over the UK for July 19th among ClimateDT members(top), ERA5 reanalysis (bottom-left) and HadUK-Grid/Crowdgrid (bottom centre/right)

From Figure 20 we first can look at how reanalysis reflects our gridded station datasets. ERA5 reanalysis is colder than HadUK-Grid, which is colder than CrowdGrid. All three agree that the peak of the heatwave was over the East of England region, although ERA5 lacks then extension down to London seen in the gridded observations, most likely due to ERA5's coarse resolution and lack of urban land scheme. The Tmax recorded in ERA5-Land (38.4 C) is also lower than the gridded station obs (40.9 °C or 41.3 °C, for HadUK-Grid or CrowdGrid), which is likely for the same reasons. It is important to note that July 19th attracted widespread media attention in the UK for being the first "40 degree day" in UK recorded history, and this is an important event to capture correctly in both magnitude and extent.

ClimateDT fails to capture the magnitude, but is adequate in extent, over all three scenarios. While there is a clear warming signal between DT-control, DT-Present, and DT-GWL2K, the Tmax for DT-Present remains 4.5 C below the observed maximum (36.2 C vs 40.9 C). On spatial extent, while ClimateDT captures the east/west split of the heatwave, it focuses hotspots on urban areas, a reflection of its better land scheme. It however does not capture the hotspot around the East of England present in ERA5 and the gridded obs.

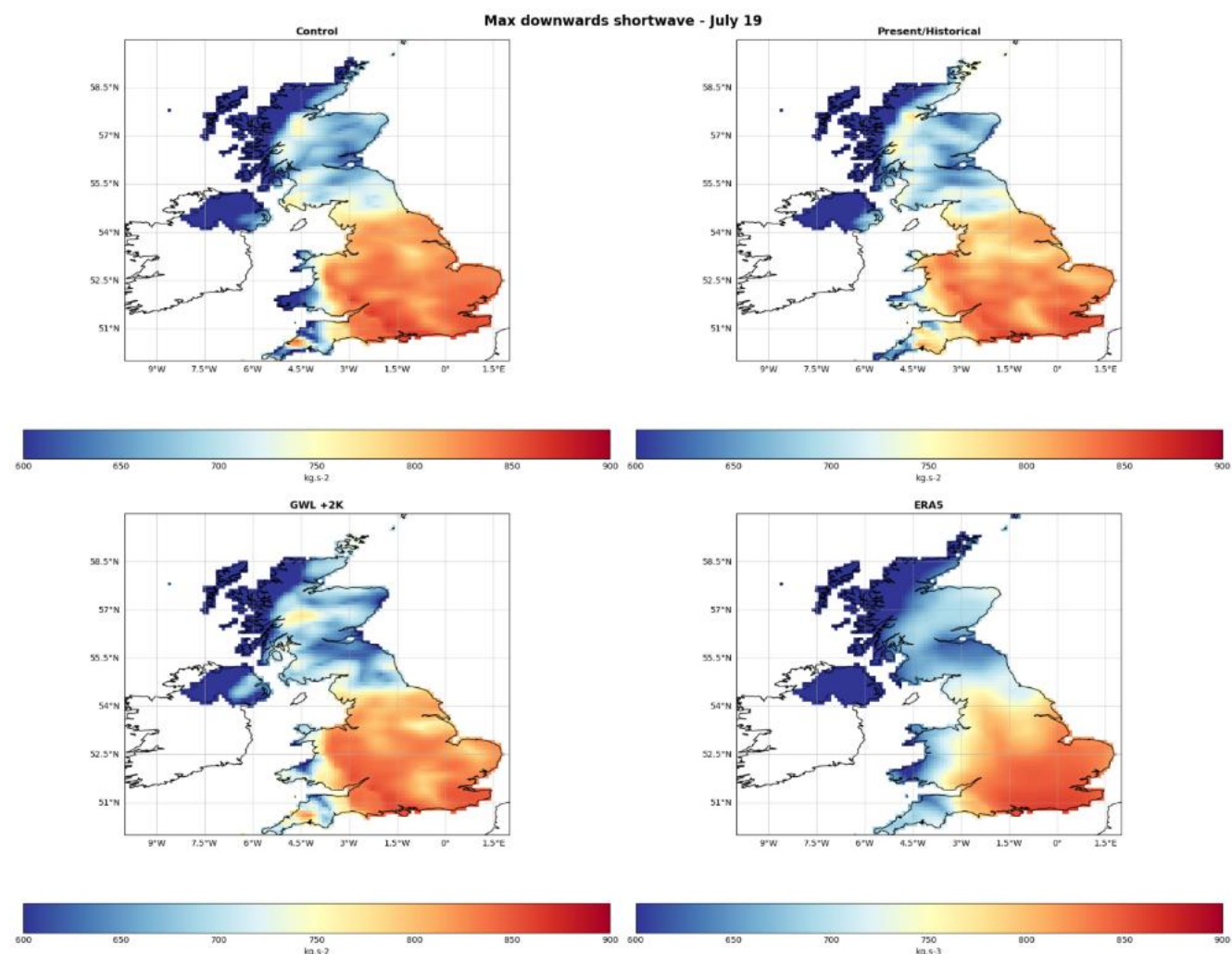


Figure 21: Maximum daily shortwave radiation on July 19th for ClimateDT storylines (top, bottom-left) and ERA5 (bottom-right)

Comparing maximum downwards shortwave (direct energy from sunlight) between ClimateDT and ERA5-Land for July 19th (Figure 21) shows a better performance for ClimateDT. The higher spatial resolution of ClimateDT has allowed it to capture cloud structures that would block incoming shortwave better than ERA5-Land (as the shortwave is just smoothed ERA5), which is an important contributor to STF-JULES outputs, while the magnitudes are substantially similar.

To investigate the cold bias present in the ClimateDT simulations, we examined the ocean temperatures compared to OSTIA observations, and the Generation 2 of ClimateDT simulations with a 5-member ensemble, to determine if either colder oceans or internal variability were an easily explainable source of bias. Neither factor was an identifiable cause, with ClimateDT oceans being warmer than observed for the period and the generation 2 ensemble having a more pronounced cold bias in the present-day simulations than the generation 1 simulation (Figure 22) - reasons for which are under investigation. We also note that a mean cold bias in

ClimateDT of around 1°C is noted in other work⁵³ and that the observed record shows that 1 C of mean warming leads to a difference of 4C-5C warming during UK heatwave events⁵⁶.

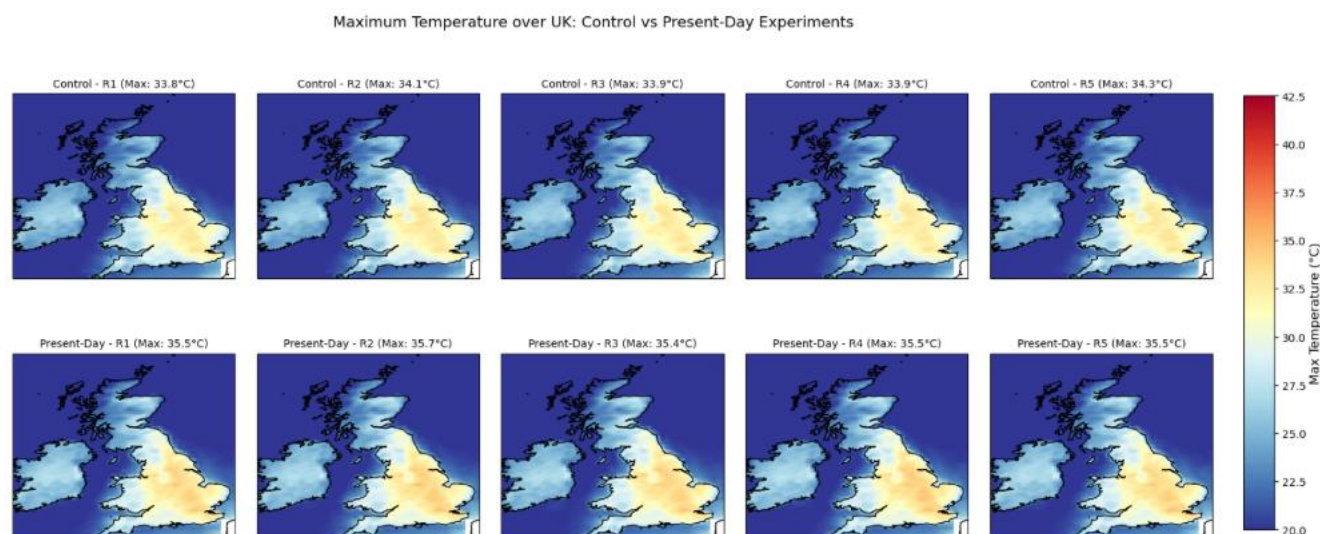


Figure 22: Maximum temperatures on July 19th for ClimateDT storyline ensemble. Control (top) member contrasted against its present (bottom) member in the ensemble

Because of this pronounced cold bias in ClimateDT, it was determined that to use ClimateDT as the factual and counterfactual climates directly would lead to misleading results, as the digital twin fails to capture the intensity of the recorded heatwave event. Instead, the mean difference (delta) between the Control and Present-Day ClimateDT simulations for rail temperature at each point will be applied to the ERA5 reanalysis baseline rail temperature outputs. This allows us to capture the warming signal and spatial resolution benefits of ClimateDT without the major cold bias distorting our results.

4.3.2. Additional impact simulations (opt)

Rail Impact Model

The impact model used for this study is the operational-timescale surface transport model developed by the Met Office known as STF-JULES. This is a modified version of the Joint UK Land Environment Simulator (JULES), the community land surface model integrated into the Met Office Unified Model for coupled atmospheric weather and climate modelling, which can also be used as a stand-alone land surface model driven by forecast output from NWP models⁵⁷. It is the latter mode, which is used for operational surface transport forecasting, to generate sector-specific forecasts from NWP model data. The STF-JULES model will shortly become operationally used for road and rail forecasting by the Met Office. This physical modelling approach is expected to be a significant step forward from the common industry practice, of estimating rail temperature to be 1.5x the air temperature at the time.

⁵⁶ Hawkins, E., Sutton, R., & Kendon, M. (2026). *Communicating changes in the intensity of UK heatwaves*. *Weather*, 81(5), 154–159. <https://doi.org/10.1002/wea.70062>

⁵⁷ Best, M. J., Pryor, M., Clark, D. B., Rooney, G. G., Essery, R. L. H., Ménard, C. B., Edwards, J. M., Hendry, M. A., Porson, A., Gedney, N., Mercado, L. M., Sitch, S., Blyth, E., Boucher, O., Cox, P. M., Grimmond, C. S. B., & Harding, R. J. (2011). *The Joint UK Land Environment Simulator (JULES), model description – Part 1: Energy and water fluxes*. *Geoscientific Model Development*, 4(3), 677–699. <https://doi.org/10.5194/gmd-4-677-2011>

Since JULES was originally developed to describe land surface interactions for application to atmospheric modelling, several extensions have been made to the physics of the model to enable its use for the bespoke purpose of generating forecasts of road and rail surface temperatures. An extra surface tile type - “road/rail” - has been developed by adjusting the properties of the standard urban tile to better represent those of a single piece of track/tarmac rather than a grid box average. This has involved both modification of physical parameters (such as emissivity, albedo, and conductivity), as well as the implementation of a new water run-off scheme and a new soil moisture scheme to treat tracks as impermeable barrier with run-off due to camber, and adjustments to how snowmelt is treated to match this.

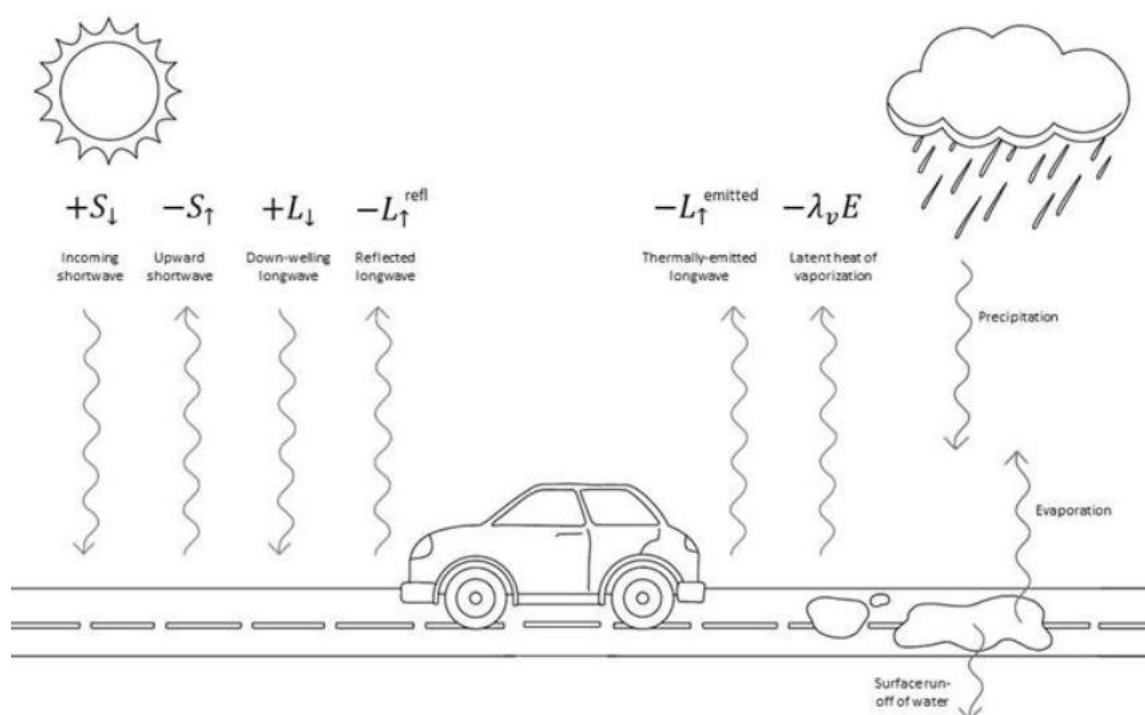


Figure 23: Schematic representing surface energy fluxes and water balance calculations in the STF-JULES model for a tarmac road.

The STF-JULES system is driven by hourly-resolution spot input data, and from this produces site-specific output at the locations corresponding to the provided input data. Input data is generated from gridded NWP data by selecting the nearest grid-point to the site in question. The specific atmospheric forecast parameters required to run the STF-JULES model are:

- Surface air temperature (K)
- Downward flux of shortwave radiation (W m^{-2})
- Downward flux of longwave radiation (W m^{-2})
- Wind speed (m s^{-1})
- Specific humidity (kg kg^{-1})
- Air pressure (Pa)
- Rainfall rate ($\text{kg m}^{-2} \text{s}^{-1}$)
- Snowfall rate ($\text{kg m}^{-2} \text{s}^{-1}$)

For this study, sites have been defined as points every 5km along the rail network over a subset of the England rail network, totalling 1800 points. Input data from each site has been taken directly from the data for that grid cell without adjustment or interpolation. This allows detailed analysis of individual train lines to identify specific lines at risk.

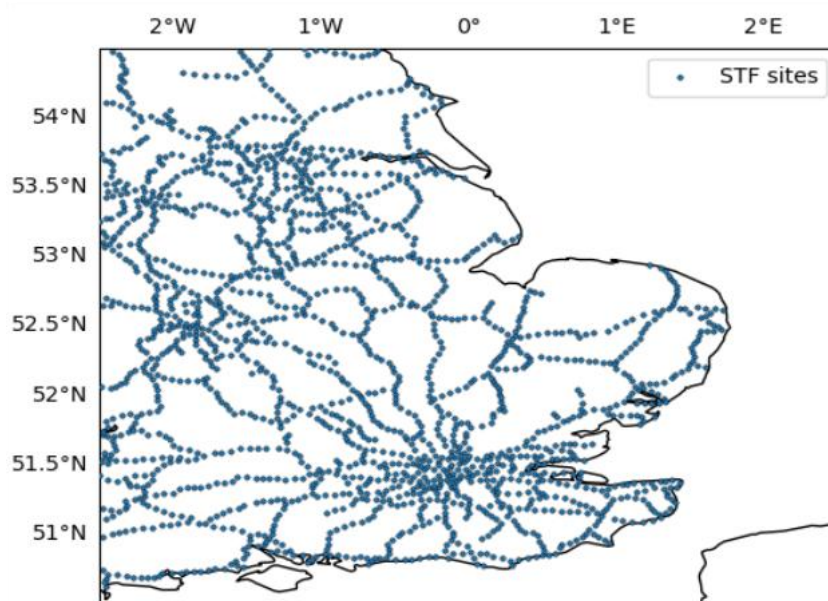


Figure 24: Map of selected rail sites for STF-JULES rail model

To demonstrate the multivariate nature of rail temperature, we performed a post-hoc global sensitivity analysis of rail temperature outputs from STF-JULES using a Random Forest methodology⁵⁸

⁵⁸ Breiman, L. (2001). *Random forests*. Machine Learning, 45(1), 5–32. <https://doi.org/10.1023/A:1010933404324>.

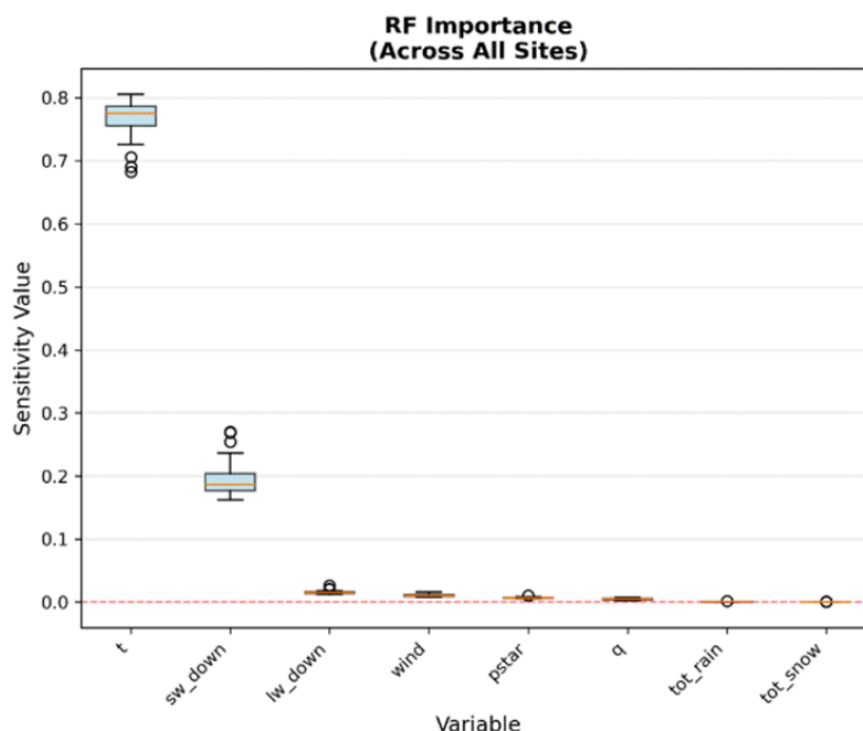


Figure 25: Random Forest sensitivity analysis results for the STF-JULES rail temperature model

These results show, when constructing a random forest model to replicate the results of the STF-JULES physical impact model at 100 random sites, the sensitivity of each variable to the final output of the random forest model, where all sensitivities must sum to 1 (total correlation $R = 0.994$). The main result to take from this is that rail temperature in the STF-JULES model is predominantly bivariate – with air temperature and shortwave radiation together describing 95% of the variation in results of the impact model.

Impact threshold

To simulate the impact of the heatwave event on the rail sector in factual and counterfactual scenarios, a temperature-based impact threshold is derived using observed disruption data. This method was deemed appropriate due to temperature's dominance in the sensitivity analysis, though a logical refinement would be the use of a bivariate threshold including temperature and shortwave radiation which cover 95% of rail temperature variability. Daily records of planned and cancelled trains, including both partial and full cancellations, were provided by the Office of Road and Rail (ORR) for the period April 2022 to April 2023⁵⁹ and we are grateful for this support. We restrict this data between June and August 2022 to focus on the summer heatwave period. This data is combined with modelled rail temperatures from the Surface Transport Forecasting (STF-JULES) model.

Daily cancellation rates were calculated for each Network Rail region and compared against corresponding daily maximum rail temperatures (Figure 27). This comparison reveals that the East Coast and London North West (LNW) South regions (see Figure 26) see both the highest rail temperatures and the greatest cancellation rates, and are therefore selected as case study regions for assessing heat-related disruption.

⁵⁹ Office of Road and Rail, data received February 2026. Available at: <https://dataportal.orr.gov.uk/about-this-site/sitemap>

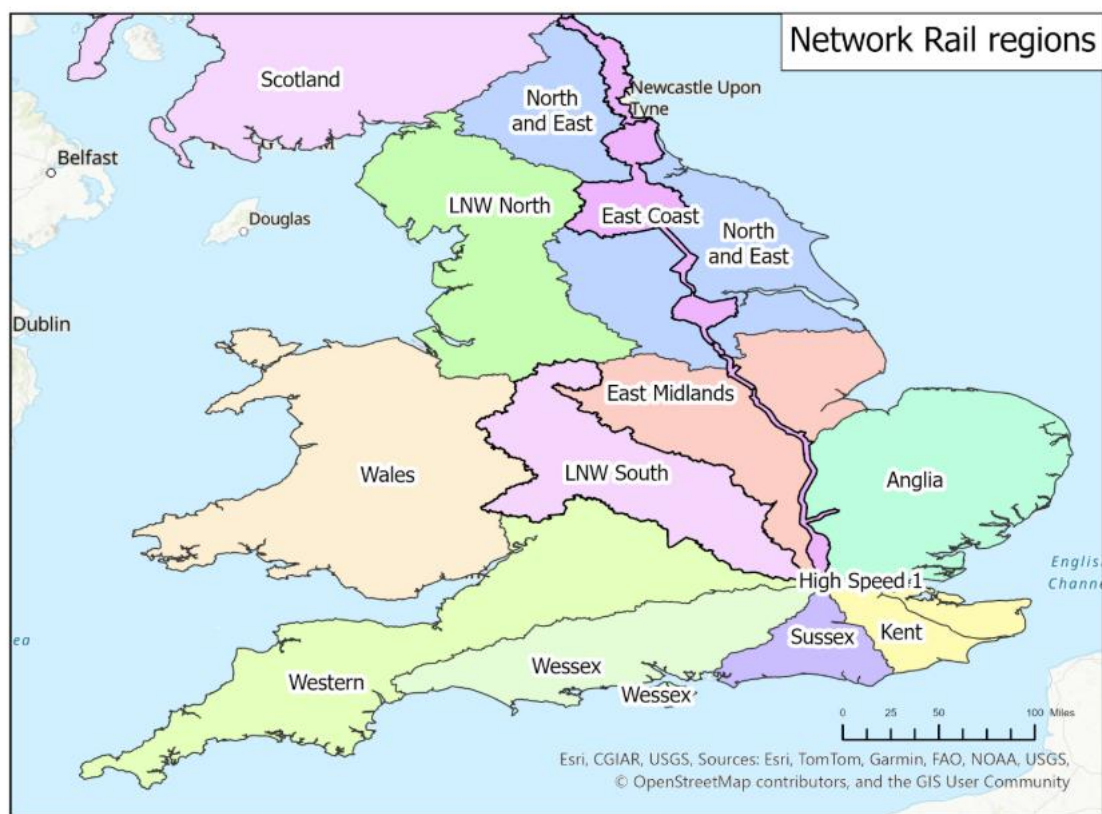


Figure 26: Network Rail regions. The two regions highlighted in bold (East Coast and LNW South) are the chosen case studies.

To establish an impact threshold, we focus on the extreme heatwave event of 18th-19th July 2022. During this period, we observe a marked increase in cancellation rates coinciding with a peak in rail temperatures. This event was compared with other high-temperature periods where cancellation rates were comparatively lower. Based on this comparison, a range of threshold temperatures were defined for each region to represent the onset of significant disruption.

To isolate the effects of extreme heat, we removed cancellations associated with known non-weather-related causes, including rail strikes and severe disruption days identified in Office of Rail and Road records⁶⁰. However, the cancellation dataset did not contain information on the specific cause of individual cancellations during the heatwave period. Consequently, while the remaining cancellations are more likely to be heat-related, they cannot be attributed solely to extreme rail temperatures. Other causes, such as signalling failures, train crew issues and trespassing, may have contributed. As such, the identified thresholds should be interpreted as temperatures at which the likelihood of rail disruption increases, rather than as temperatures that directly cause cancellations.

For the East Coast region, the threshold was estimated to be between 49-50°C, and for LNW South, 48-50°C (Figure 27).

⁶⁰ Office of Rail and Road (2022). *Passenger rail performance: July to September 2022*. Office of Rail and Road, 8 December 2022. Available at: <https://dataportal.orr.gov.uk/media/2165/passenger-performance-jul-sep-2022.pdf>.

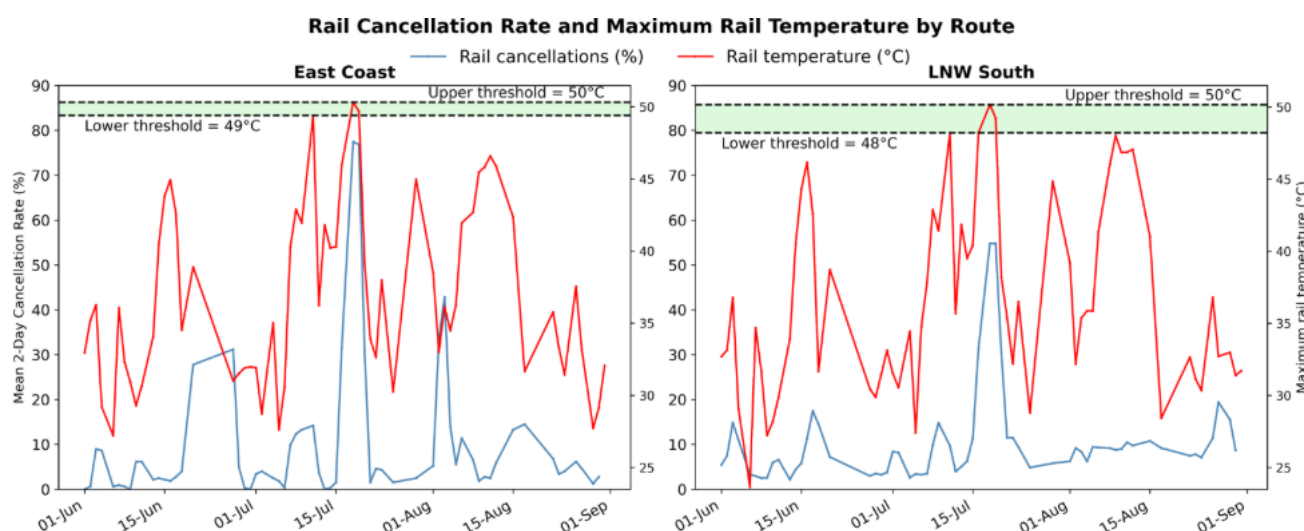


Figure 27: Comparison of regional cancellation rate (%) and daily maximum rail temperature to determine impact thresholds for East Coast and LNW South regions.

These thresholds are subsequently applied to ERA5 rail temperature datasets for both factual and counterfactual scenarios. For each scenario, the number of days exceeding the specified thresholds is calculated. By comparing exceedance rates across the different scenarios, it is possible to assess the extent to which anthropogenic climate change has contributed to the heat-related disruption to the rail network on 18-19th July.

Exposure

To investigate changes in exposure, existing literature and reports from the Office of Rail and Road (ORR) and the Department for Transport (DfT) are used to assess long-term trends in rail usage. This is complemented by a high-resolution dataset from the ORR, which provides station-level information on annual entries and exits across the UK from around 2000 to the present day⁶¹. We use this data to explore how rail usage has changed between 2000 and 2022 and to assess how changes in passenger numbers may have altered the number of people exposed to the impacts of extreme heat-related rail disruption in 2022.

Station usage from 2000 is used to construct a counterfactual exposure scenario, representing a time where fewer people used the railway. This allows us to simulate how many people might have been affected by an extreme heat event if the same hazard had occurred under past levels of rail demand. We use this information to separate the influence of changing exposure to changes in hazard intensity.

Using this data, maps are produced to illustrate the spatial variation in changes in rail usage over time. These will identify areas where increases in passenger activity could have amplified rail disruption, supporting our assessment of how changes in exposure may influence the overall impact of an extreme drought-heatwave event.

Vulnerability

We qualitatively assess the vulnerability of the UK rail network to extreme temperatures and drought with support from existing literature. Our assessment focuses on both the physical infrastructure of the UK network and its dependence on external networks.

⁶¹ Office of Rail and Road (2023). *Estimates of station usage 2022–23*. Office of Rail and Road. Available at: <https://dataportal.orr.gov.uk/statistics/usage/estimates-of-station-usage/>

4.4. Results

4.4.1. Factual and impact results

Under factual conditions, widespread exceedances of the impact thresholds occur during summer 2022 along the East Coast Main Line (ECML) and London North West (LNW) South route (Figure 28). The greatest concentrations of exceedances are observed along the ECML and around Birmingham within LNW South.

Exceedances become progressively less widespread as the threshold increases. At the 48 °C threshold, most of the LNW South route exceeds the threshold on at least one summer day, with notable hotspots around London and south of Birmingham. In contrast, exceedances of the 50 °C threshold are highly localised and occur only in limited sections of the ECML and near Birmingham. These extreme rail temperatures were reached on 18th July 2022, coinciding with the hottest days of the heatwave.

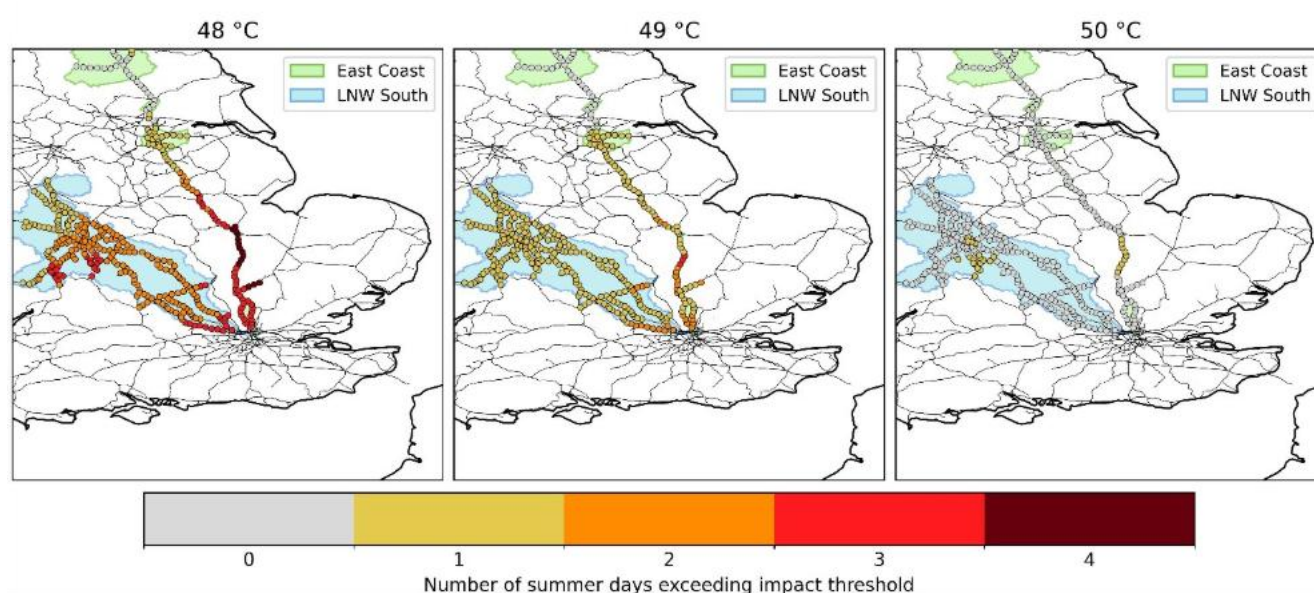


Figure 28: Exceedance of impact thresholds in factual scenario.

4.4.2. Attribution results

In the counterfactual scenario, exceedances of the impact thresholds (48 °C, 49 °C, and 50 °C) do not occur anywhere within the case study regions (East Coast and LNW South) during the summer of 2022 (Figure 29).

While this is only from a single Generation 1 DestineE storyline simulation, the Generation 2 5-member ensemble all have a lower maximum temperature for the heatwave than the Generation 1 member (by 0.5-0.7 °C). They all also have a smaller difference between their control and present-day rail temperature simulations for July 2022 heatwave (1.2C-1.7°C) than the Generation 1 member used for this study (2.3°C) due to the differences in ocean initialization and emission scenario used, which may alter the results slightly.

Despite being below the impact thresholds, rail temperatures in the counterfactual scenario still approach 47.5 °C, suggesting that some level of disruption would likely have occurred even in the absence of post-1950 human-induced climate change. Based on the observed rail temperature and cancellation rates during summer 2022, counterfactual cancellation rates may have been approximately 30-35% on the ECML and 15-20% on LNW South. Although substantially lower than those observed in the factual scenario, these disruption levels would still exceed Network Rail's threshold for a severe disruption day, defined as 5% of services cancelled⁶¹.

This allows us to conclude that under the specific meteorological conditions which led to the July 2022 drought-heatwave, the observed severe rail disruption (~75% cancellations on ECML and ~55% on LNW South) is attributable to the influence of anthropogenic climate change since 1950.

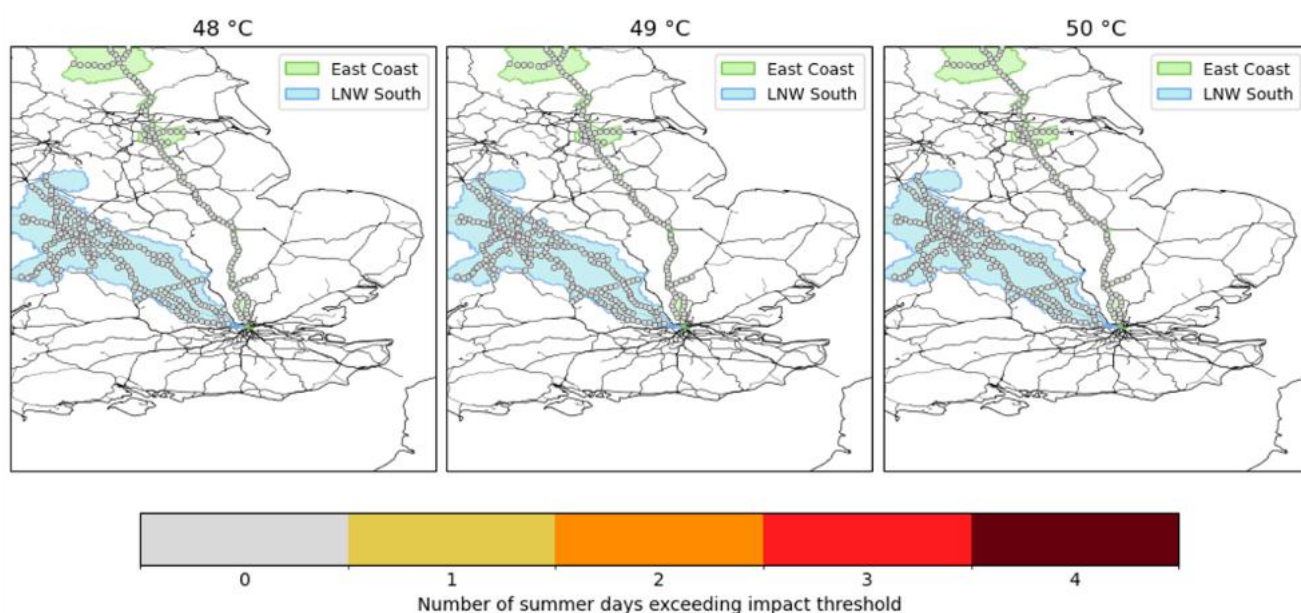


Figure 29: Exceedance of impact thresholds in counterfactual scenario.

Exposure

Alongside changes in the climate hazard, growth in rail travel since the 1980s has significantly increased exposure to the impacts of extreme heat events. Passenger journeys almost doubled in the past 20 years leading up to the COVID-19 pandemic, recording a peak of 1.8 billion journeys in 2018-2019⁶².

Although passenger numbers fell sharply during the pandemic, rail usage has steadily recovered. Between 2022-2023 and 2024-2025, annual passenger journeys increased from nearly 1.4 billion to around 1.7 billion, approaching pre-pandemic levels⁶². It should be noted that rail demand was impacted for several years after the pandemic. Had COVID-19 not occurred, passenger numbers, and hence the number of people affected by the July 2022 drought-heatwave, would have likely been significantly higher.

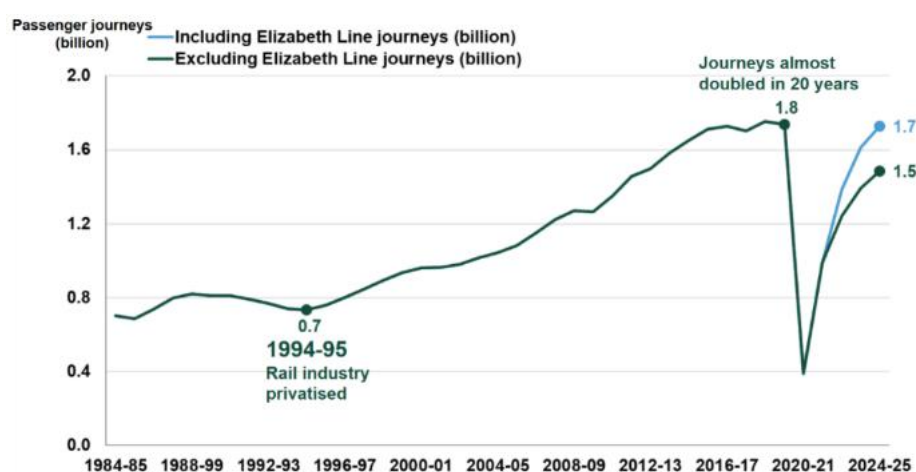


Figure 30: Annual national passenger journeys (billion) between April 1984 to March 2025, showing both including and excluding the Elizabeth Line⁶².

⁶² Office of Rail and Road (2025). *Passenger rail usage 2024–25*. Office of Rail and Road. Available at: <https://dataportal.orr.gov.uk/statistics/usage/passenger-rail-usage/>

Comparing rail usage in 2022 to the baseline usage of 2000 shows that rail usage has increased nationally, but growth has not been uniform. Figure 31 illustrates changes in regional station usage between 2000 and 2022. The largest growth has occurred in Anglia and London North West (LNW) North, where station usage has more than doubled, increasing by 108%.

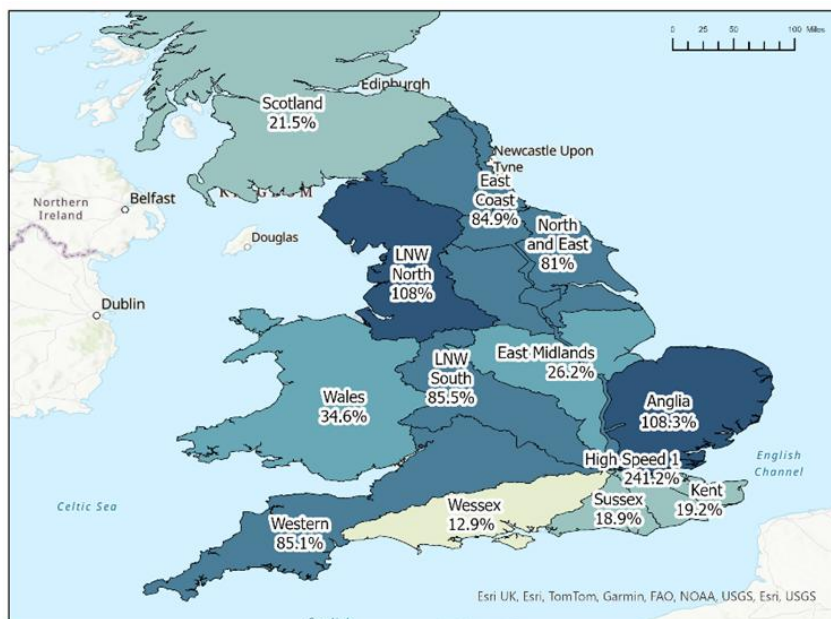


Figure 31: Change (%) in regional station usage between 2000 and 2022.

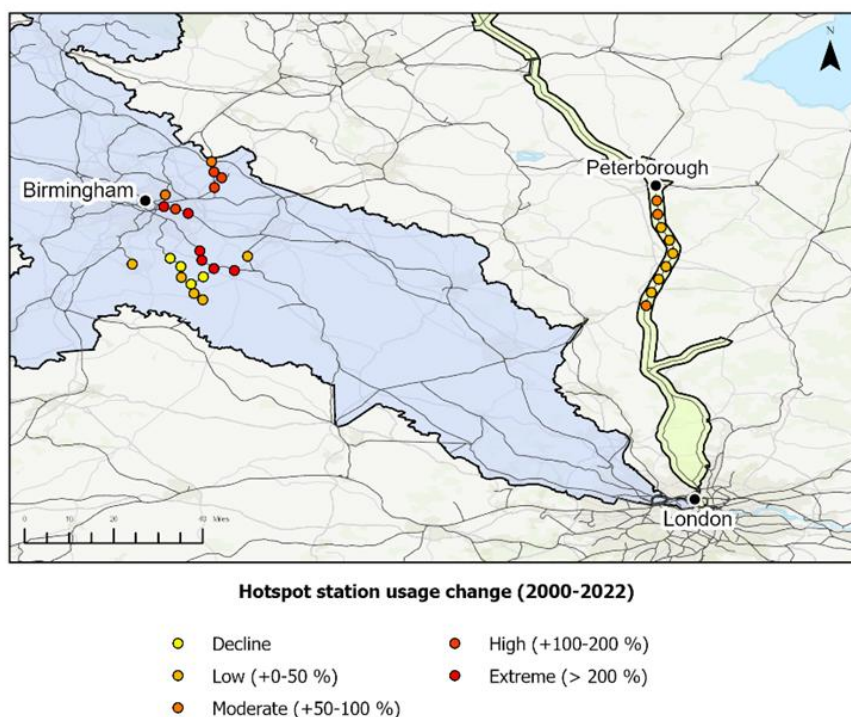


Figure 32: Change in station usage between 2000 and 2022 which were closest to parts of the railway exceeding 50 °C during the July 2022 drought-heatwave.

Focusing on the most impacted regions in the July 2022 heatwave, East Coast and LNW South, Figure 32 indicates that locations where rail temperatures exceeded 50 °C correspond closely with stations that have experienced some of the largest increases in passenger demand.

Stations within LNW South recorded particularly strong growth. For example, usage at Warwick Parkway increased by approximately 450% between 2000 and 2022, while Hatton and Marston Green experienced increases of 290% and 280% respectively (see Figure 33). As a result, the 2022 drought-heatwave affected a much larger number of passengers than a comparable event would have in 2000, highlighting that increased exposure was a contributor to the severity of the 2022 rail disruption. Had a similar drought-heatwave occurred in 2000, lower passenger numbers would likely have reduced overall exposure to disruption and, consequently, the scale of its impacts.

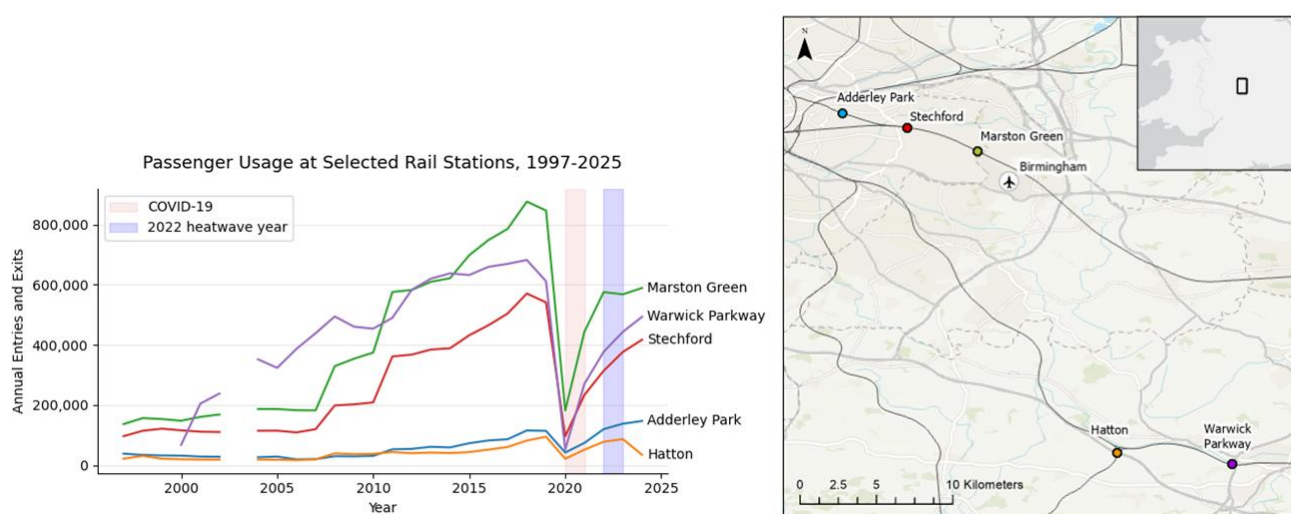


Figure 33: Timeseries of passenger usage of stations with the highest % change in usage between 2000 and 2022 (left). Map showing the location of selected stations (right).

Looking into the future, several scenarios for rail growth above pre-pandemic levels have been identified by the Railway Industry Association (RIA), with growth between 37% and 97% by 2050, depending on government policies (Figure 34)⁶³. Data from 2023-2024 showed rail demand increased by 16%, with a further 7.2% in 2024-2025 which is in line with the most extreme growth scenario. As extreme heat events become more common and more intense, this will combine with increased exposure of railway users, potentially leading to greater disruption and wider societal impacts.

⁶³ Railway Industry Association (2025). *Future of Rail: Demand: Summary of discussions January 2025*. Railway Industry Association. Available at: <https://www.riagb.org.uk/RIA/RIA/Newsroom/Publications%20Folder/Discussion-Paper-Future-of-Rail-Demand.aspx>.

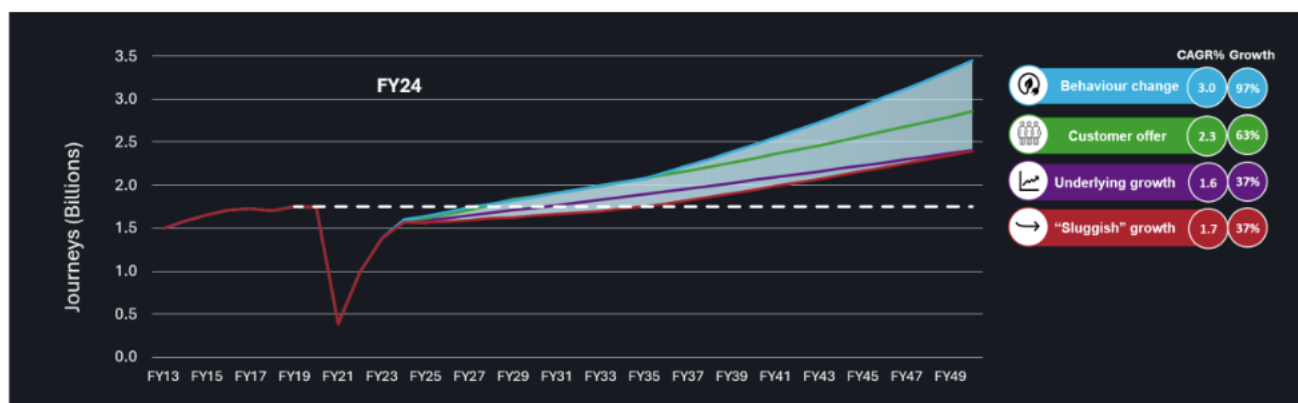


Figure 34: Future scenarios of rail growth in the UK. Graph from RIA (2025) report⁶³.

Passenger services are only one part of this challenge. Rail freight plays a critical role in transporting goods throughout the UK and is expected to become increasingly important in delivering the UK's net-zero ambitions by reducing reliance on road haulage. The RIA estimates that an additional 450 freight trains per day will be required to achieve the government's target of 75% rail freight growth by 2050⁶³. Greater dependence on rail freight, combined with an increased number of trains, means that future heat-related disruptions could have wider economic consequences through delays to the movement of goods and services.

With a significant push towards sustainable travel, travelling by rail will become an increasingly popular and important mode of transport for both passengers and rail freight. Consequently, exposure to future heat events is expected to rise, potentially increasing the scale of disruption and overall impact of extreme heat impacts on the UK rail network.

Vulnerability assessment

A key vulnerability of the rail network stems from the thermal tolerance of the tracks. UK railways are designed to a stress-free temperature of 27 °C, the UK mean summer rail temperature⁶⁴. This temperature is chosen so that the railways can withstand both summer and winter conditions. However, during extreme heat events, rail temperatures can exceed design limits causing rails to expand and buckle, which is what happened at multiple locations during the July 2022 drought-heatwave. The track's ability to cope with heat is also dependent on its condition with certain track types having a higher tolerance than others. For example, tracks described as "severe shortage of ballast between sleepers or sleepers are exposed" will start to see interventions when rail temperatures reach 31 °C with severe speed restrictions of 20 mph enforced at 34 °C. In contrast, well-maintained, higher quality track, such as "undisturbed, fully ballasted and consolidated track", sees interventions start at 53 °C and 20 mph restrictions at 63 °C⁶⁵. This highlights the importance of track condition in determining the severity of heat-related impacts.

Another important vulnerability relates to the earthworks supporting the railway. Clay embankments are particularly susceptible to drought, as they shrink when soil moisture is depleted, increasing the risk of ground movement and track deformation. Vulnerable routes include the West of England Line between Basingstoke and

⁶⁴ Network Rail (2023). *Why rails buckle in Britain*. 9 June 2023. Available at: <https://www.networkrail.co.uk/stories/why-rails-buckle-in-britain/>

⁶⁵ Palin, E. J., Thornton, H. E., Mathison, C. T., McCarthy, R. E., Clark, R. T., & Dora, J. (2013). *Future projections of temperature-related climate change impacts on the railway network of Great Britain*. *Climatic Change*, 120, 71–93. <https://doi.org/10.1007/s10584-013-0810-8>

Exeter St Davids and the c2c line connecting East London and South Essex⁶⁶. Drought-induced soil moisture deficit can therefore act as a compounding hazard, amplifying the impacts of extreme heat. This impact was well documented during summer 2025 when prolonged speed restrictions and timetable reductions were imposed between London Waterloo, Yeovil Junction and Exeter due to drought-related ground subsidence. This disruption lasted for several months until soil moisture levels recovered⁶⁶.

The increasing electrification of the railway also introduces additional vulnerabilities. Around 38% of the network was electrified in 2022, rising to 39% by 2025⁶². Overhead line equipment can begin to experience performance issues when temperatures exceed 33°C, meaning that more than one-third of the network is currently exposed to heat-related electrical failure⁶⁵. With plans to achieve near-complete railway electrification by 2050 as part of the UK's net-zero ambitions, a growing proportion of the network will rely on infrastructure that is sensitive to extreme heat.

In addition, the wider transport system is vulnerable because of its interconnected nature. Rail services provide critical links to major airports, meaning train disruption can quickly propagate beyond the railway, for example, increasing the risk of passengers missing flights. Figure 35 shows that sections of railway exceeding 49°C during the 2022 heatwave were located close to major UK airports. Particularly vulnerable areas are around Birmingham International Airport. Marston Green, the busiest station among the identified heat hotspots, lies immediately before the airport on the route from Birmingham New Street (Figure 35). Notably, three of the five hottest locations identified within the LNW South region are situated on this route. As a result, heat-related disruption along this stretch of track has the potential to directly affect airport accessibility, demonstrating how failures on the rail network can have cascading impacts across the wider transport system.

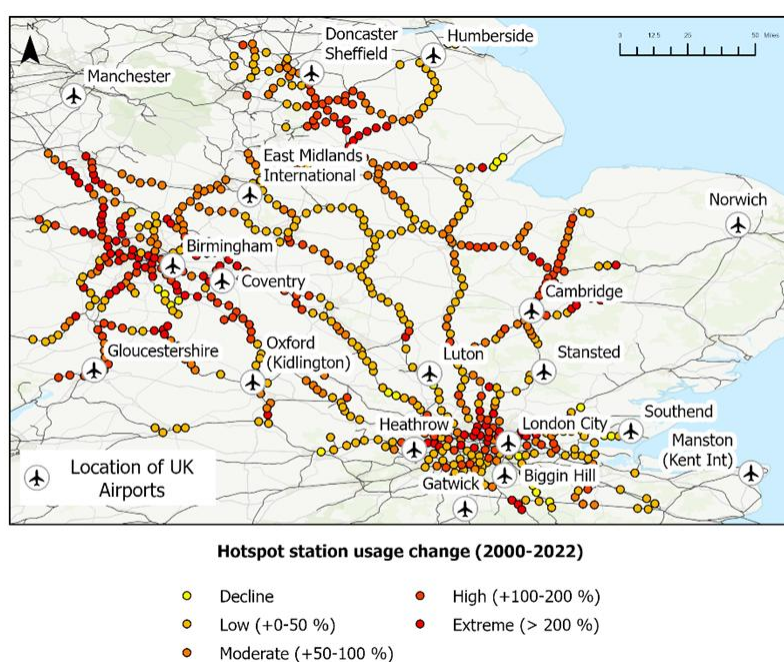


Figure 35: Change in usage of stations nearest to railway locations exceeding 49 °C during the July 2022 drought-heatwave and their proximity to UK airports.

⁶⁶ Network Rail. (2025). *What is soil moisture deficit and why does it affect train services?* Available at: https://www.networkrail.co.uk/stories/soil-moisture-deficit-on-the-railway/?cat_name=industry-leading

4.4.3. Stakeholder and policy relevance

The July 2022 drought-heatwave was a monumental event for the UK and exposed the inherent vulnerability within the transport sector. Our study shows that without the influence of anthropogenic climate change since 1950, the rail disruption on 18-19th July would've been substantially less severe under similar synoptic conditions. Increased usage of the rail network since 1980 is likely to have amplified the overall impact of the event as more passengers were exposed to heat-related disruptions. Similarly, the interconnected nature of UK transport systems means that impacts on one sector can quickly cascade to another, compounding the disruption.

Since 2022, the UK rail sector has made substantial effort to improve the resilience of the network to extreme heat. Several independent reviews were commissioned to look at Network Rail's response to the July 2022 extreme heat event and offered recommendations on how they can respond and adapt to events like this in the future⁶⁷.

Network Rail also produced their 4th Adaption Report in 2024 which states the progress they've made towards understanding the potential impacts of climate change on the performance and safety of the rail network, and the actions taken to increase resilience. Each Network Rail region has devised individual Weather Resilience and Climate Change Adaption plans, with the most recent one covering the period 2024-2029 (CP7)⁶⁸. These plans identify region-specific climate hazards, assess risks to critical assets, and set out investment priorities and adaptation measures. This regional approach reflects the differing climate vulnerabilities across the network, for example, risks on the East Coast Route differ substantially from those on the Anglia Route.

A key example is the East Coast Route, where adaptation measures focus on reducing the vulnerability of track infrastructure to extreme heat⁶⁸. Planned investments include the renewal of timber switch and crossing (S&C) assets on higher-speed lines, replacement of jointed track sections that are particularly susceptible to thermal stress, and extensive track renewal programmes. Additional investment is being directed towards signalling modernisation, including digital signalling on the East Coast Main Line, which reduces the reliance on vulnerable lineside equipment and improves resilience to a range of climate hazards, including heat, flooding, and high winds.

Climate adaptation measures also extend to earthworks management. Increasingly prolonged periods of hot, dry weather can lead to soil desiccation, particularly in clay and peat embankments, causing ground movement and track geometry defects. In response, Network Rail is developing improved monitoring and intervention strategies, including the use of Soil Moisture Deficit (SMD) indicators to provide early warning of potential asset instability and allow preventative action before service disruption occurs⁶⁸.

Our findings reinforce the importance of these adaptation efforts. As climate change increases the likelihood, duration, and intensity of extreme heat events, and demand for rail travel continues to grow, maintaining and enhancing the resilience of transport infrastructure will be critical. Climate adaptation, monitoring technologies, and operational planning will be essential to minimise future disruption and ensure the reliability and safety of the UK's railway network under a changing climate.

Stakeholder engagement workshops

⁶⁷ Network Rail. (2025). *Responding to weather impacts on the railway*. Network Rail. [Network Rail — Responding to weather impacts on the railway](#)

⁶⁸ Network Rail. (2024). *Annual report and accounts 2024*. <https://www.networkrail.co.uk>

Deliverable 4.2 – Hazard and Impact Synthesis and Attribution for Phase II use case

- Some engagement with stakeholders from the UK's Department for Transport (DfT) was completed early in the project development to understand areas of vulnerability along the rail network. This helped refine the case study regions most impacted during the 2022 heatwave.

Dissemination

- Dissemination of outputs will be in the form of a technical summary document and/or infographic and will be shared with the DfT and Network Rail to assist in understanding of extreme heat risk to UK rail network and hopefully benefit mitigation and adaption strategies.

5. Use case 3: East Africa Cyclones Idai (2019) extended

5.1. Summary of findings phase 1

The Phase I use case demonstrated that climate change increased the severity of flooding associated with Tropical Cyclone (TC) Idai in Mozambique. Although flood extent increased by only 2%, climate change contributed to a 29% increase in direct economic damages and an 18% increase in the population exposed to severe flooding, illustrating how relatively small changes in hazard drivers can lead to disproportionate societal impacts. These impacts were assessed using a modelling chain consisting of the wflow hydrological model, Delft3D FM coastal hydrodynamic model, SFINCS flood model, and Delft-FIAT impact model. In Phase I, attribution was based on a storyline approach that removed estimated climate change signals from ERA5 rainfall and sea level rise to construct a counterfactual scenario.

The use case showed that while satellite-derived flood models show reasonable agreement with our data, uncertainties associated with the attribution statements are considered to be relatively high. This is partly due to model limitations and the scarcity of local observations for calibration and validation but also reflects uncertainties in the construction of the factual and counterfactual attribution scenarios that is based on a simplified approach. Reducing some of these uncertainties by improving the physical realism of the attribution scenarios is therefore a key focus of the Phase II extension.

5.2. Objective of extension

In Phase 2 we revisit the use case of TC Idai flooding in Sofala, Mozambique, and explore an alternative climate attribution method, which is based on the nudged climate storylines dataset available from the Destination Earth ClimateDT project^{69,70}. We explore the strengths and limitations of the climate attribution approach grounded in nudged climate storyline simulations by using these alternative factual and counterfactual scenarios for a major historical flood event. We aim to advance understanding of whether flood hazard modelling for an individual extreme event can be robustly performed using ClimateDT storylines, and improve an understanding of uncertainty associated with this method.

5.3. Updated (attribution) modeling framework

5.3.1. Climate storylines

The ClimateDT storylines dataset allows to replay past extreme events under alternative (so-called “counterfactual”) climate conditions. This dataset situates past weather events in present-day (factual) climate and in past (ca. 1950) and future climate (at 2°C global warming). This makes it possible to assess how the characteristics of the same event would differ under alternative climate states. The dataset (as of April 2026) provides global climate model outputs for events within the period of 2017–2024 for these three scenarios, with hourly temporal resolution, based on the IFS-FESOM climate model with 9 km resolution atmospheric model and 5 km resolution ocean model^{71,72}.

⁶⁹ Shepherd, T.G., Boyd, E., Calel, R.A. et al. *Storylines: an alternative approach to representing uncertainty in physical aspects of climate change*. *Climatic Change* 151, 555–571 (2018). <https://doi.org/10.1007/s10584-018-2317-9>.

⁷⁰ Athanase, M., Sánchez-Benítez, A., Monfort, E. et al. *How climate change intensified storm Boris’ extreme rainfall, revealed by near-real-time storylines*. *Commun Earth Environ* 5, 676 (2024). <https://doi.org/10.1038/s43247-024-01847-0>.

⁷¹ *Climate Change Adaptation Digital Twin*. <https://destine.ecmwf.int/climate-change-adaptation-digital-twin-climate-dt/>

⁷² John, A., Beyer, S., Athanase, M., Sánchez-Benítez, A., Goessling, H. F., Hossain, A., et al. (2026). *Global kilometer-scale climate storylines using spectral nudging*. *Journal of Advances in Modeling Earth Systems*, 18, e2025MS005326. <https://doi.org/10.1029/2025MS005326>

The ClimateDT storyline simulations are created using a nudging approach, which constrains the large-scale atmospheric flows by ERA5 reanalysis data. The effect of climate change is realized by prescribing background climate states corresponding to three different climates (ca. 1950, ca. 2017, and 2°C global warming projections). Given that the large-scale atmospheric flow patterns are constrained, the weather patterns remain consistent in the factual and counterfactual scenarios. The drawback of this approach is that the effect of climate change on dynamic parameters (e.g. wind intensity and direction, and consequently, the cyclone tracks) are not included. Therefore, the ClimateDT storylines cannot be used to study changes in coastal storm surges and waves as a result of altered wind conditions under counterfactual climate scenarios. Here we focus on flood drivers for which the effect of climate change is expected to be realistically represented in the ClimateDT storylines, i.e. the thermodynamically affected drivers – in this case, the precipitation-related drivers of river discharges and local rainfall.

In our study we use the following scenarios:

- Factual scenario – ClimateDT storylines present climate ('historical' simulation in ClimateDT).
- Counterfactual scenario – Climate DT storylines past climate ('control' simulation in ClimateDT).

The counterfactual scenario roughly corresponds to the 1950 climate. We make the assumption that this scenario is close to the pre-industrial climate, as most of the effects of the climate change have developed after 1950 (global temperatures in 1950 were approximately 0.2°C above the pre-industrial levels, compared to roughly 1°C in 2017⁷³).

Wind and pressure fields

To understand whether the ClimateDT storylines can be used in attributing the effect of climate change to the flooding caused by TC Idai, we first explore how the tropical cyclone is represented in both the factual and counterfactual scenarios. Figure 36 compares the wind fields at the coast of Beira before and during the TC landfall. It demonstrates that the temporal dynamics of the TC Idai landfall are consistent in both scenarios, with the wind fields remaining very similar. This is further illustrated in Figure 37 which also shows that the timeseries of wind speeds and pressure at the coast of Beira are nearly identical between the factual and counterfactual simulations (as expected in nudged simulations). A comparison with ERA5 also shows a very good match of mean sea level pressure timeseries, while the magnitude of the wind speeds is higher in the ClimateDT storyline than in ERA5 reanalysis (possibly because of the higher grid resolution leading to better representation of TC wind speeds).

⁷³ IPCC (2018). *Global warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty* [V. Masson-Delmotte, P. Zhai, H. O. Pörtner, D. Roberts, J. Skea, P.R. Shukla, A. Pirani, W. Moufouma-Okia, C. Péan, R. Pidcock, S. Connors, J. B. R. Matthews, Y. Chen, X. Zhou, M. I. Gomis, E. Lonnoy, T. Maycock, M. Tignor, T. Waterfield (eds.)]. In Press.

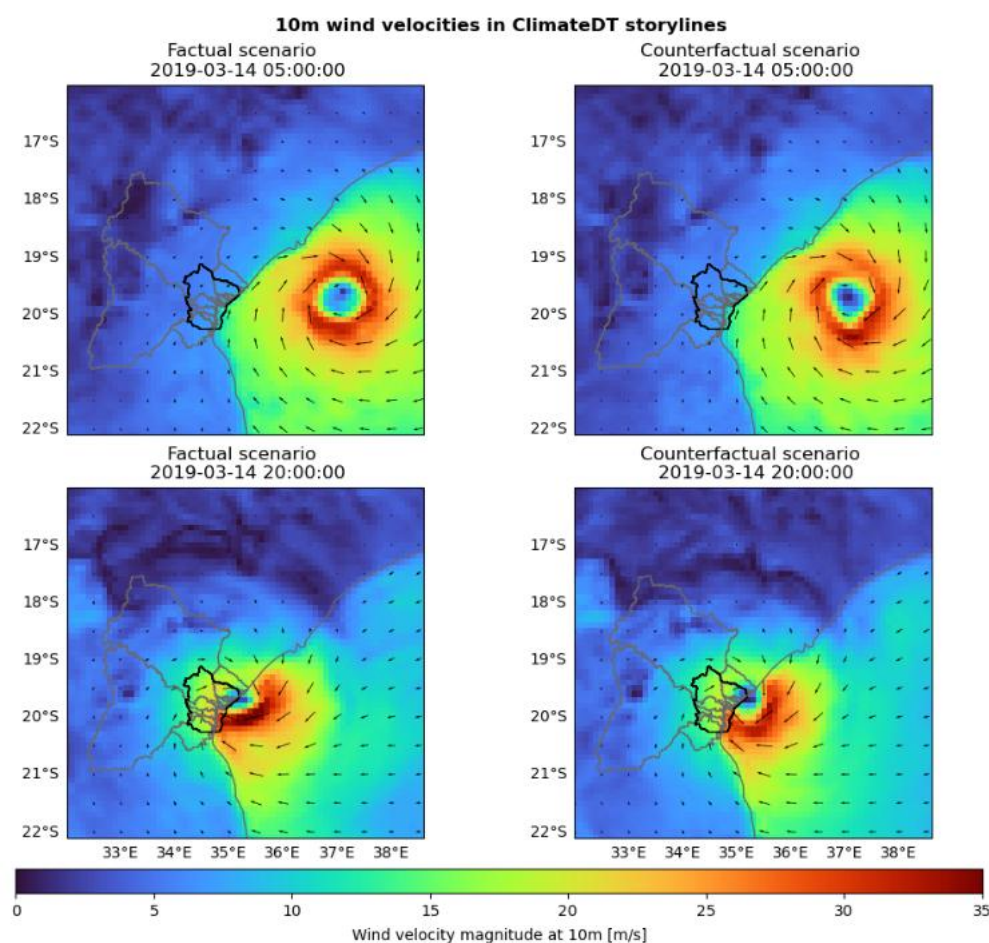


Figure 36: Wind speeds at 10m height in the factual and counterfactual scenarios from ClimateDT storylines before and during the TC Idai landfall at the coast of Beira.

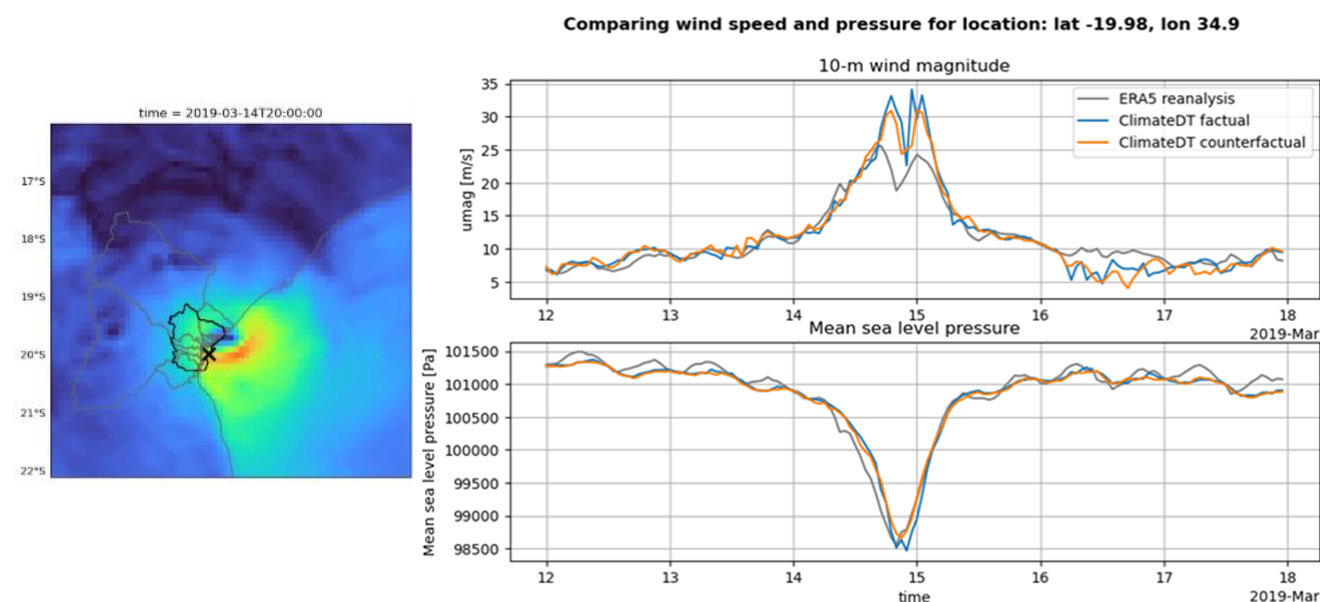


Figure 37: Wind speeds and mean sea level pressure timeseries at the coast of Beira before and after TC Idai landfall in factual and counterfactual simulations ClimateDT storyline compared to ERA5 reanalysis. The location is indicated on the left plot with a black cross marker. There are some differences between the factual and counterfactual, but there is considerable uncertainty about whether that is a climate signal given that this is the result for a single location.

Precipitation comparison across ClimateDT scenarios

ClimateDT storylines reflect the effect of changes in global temperatures on precipitation patterns. Generally, it is expected that a warmer atmosphere and ocean result in more intense precipitation during extreme events, due to increased ocean evaporation and the enhanced moisture-holding capacity of the atmosphere. ClimateDT storylines for TC Idai reflect a mean temperature difference of approximately 0.9°C in the area of interest (see Figure 45 in the Annex). The effect of global warming on precipitation during TC Idai according to ClimateDT scenarios is shown in Figure 38 and Figure 39. The area-aggregated precipitation timeseries in Figure 38 show that the precipitation timeseries are temporally very consistent between scenarios. Directly at TC landfall (14–15 March), the factual scenario contains more intense precipitation than the counterfactual scenario, with an increase of approximately 20% in precipitation volume at the precipitation peak. In the subsequent days, during the second precipitation peak on 17-18 March, the area-aggregated precipitation remains very similar between the two scenarios (with slightly larger peak precipitation in the counterfactual scenario).

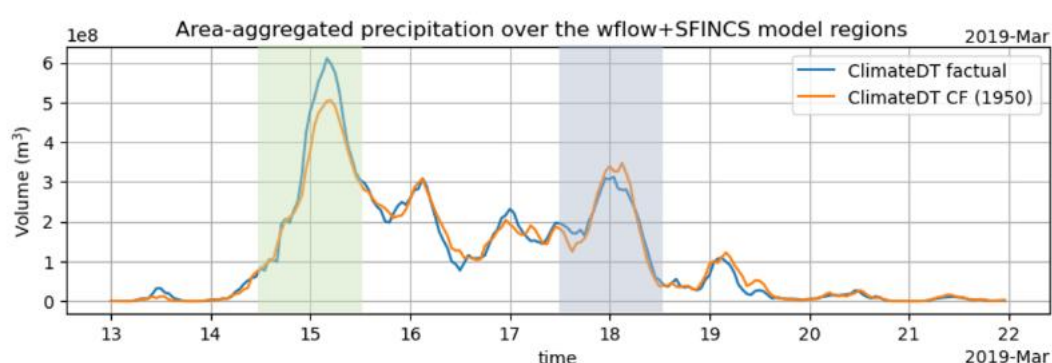


Figure 38: Timeseries of area-aggregated precipitation over the model area (hydrological and flood models). Color blocks indicate 24-hour periods around the two precipitation peaks.

Comparison of spatial distribution of precipitation presented in Figure 39 further reveals the differences in spatial distribution of precipitation between the two scenarios. During the first precipitation peak, directly at TC Idai landfall in Beira on 14-15 March, the pattern of precipitation is very similar between the scenarios (Figure 39, top), with 10% larger 24-hour precipitation volume in the factual scenario. However, during the second precipitation peak (17-18 March) the precipitation patterns are very different between the two scenarios, with precipitation being concentrated further inland in the factual scenario than in the counterfactual scenario (Figure 39, middle). The area-aggregated precipitation in the factual scenario is approximately 4% lower than that of the counterfactual scenario, and the rainfall is distributed very differently between the river catchments upstream of the flood model (less rainfall in the Buzi catchment and more in the Pungwe catchment in the factual scenario compared to counterfactual). Looking at the aggregated precipitation over the entire event in the period 10-25 March (Figure 39, bottom), we can observe that in the factual scenario more precipitation falls further inland compared to the counterfactual scenario. The mean relative difference in volume over the entire model area is, however, only 2.4% (i.e. the factual scenario cumulative precipitation is 2.4% higher than the counterfactual, where the relative percentage is calculated relative to the factual scenario).

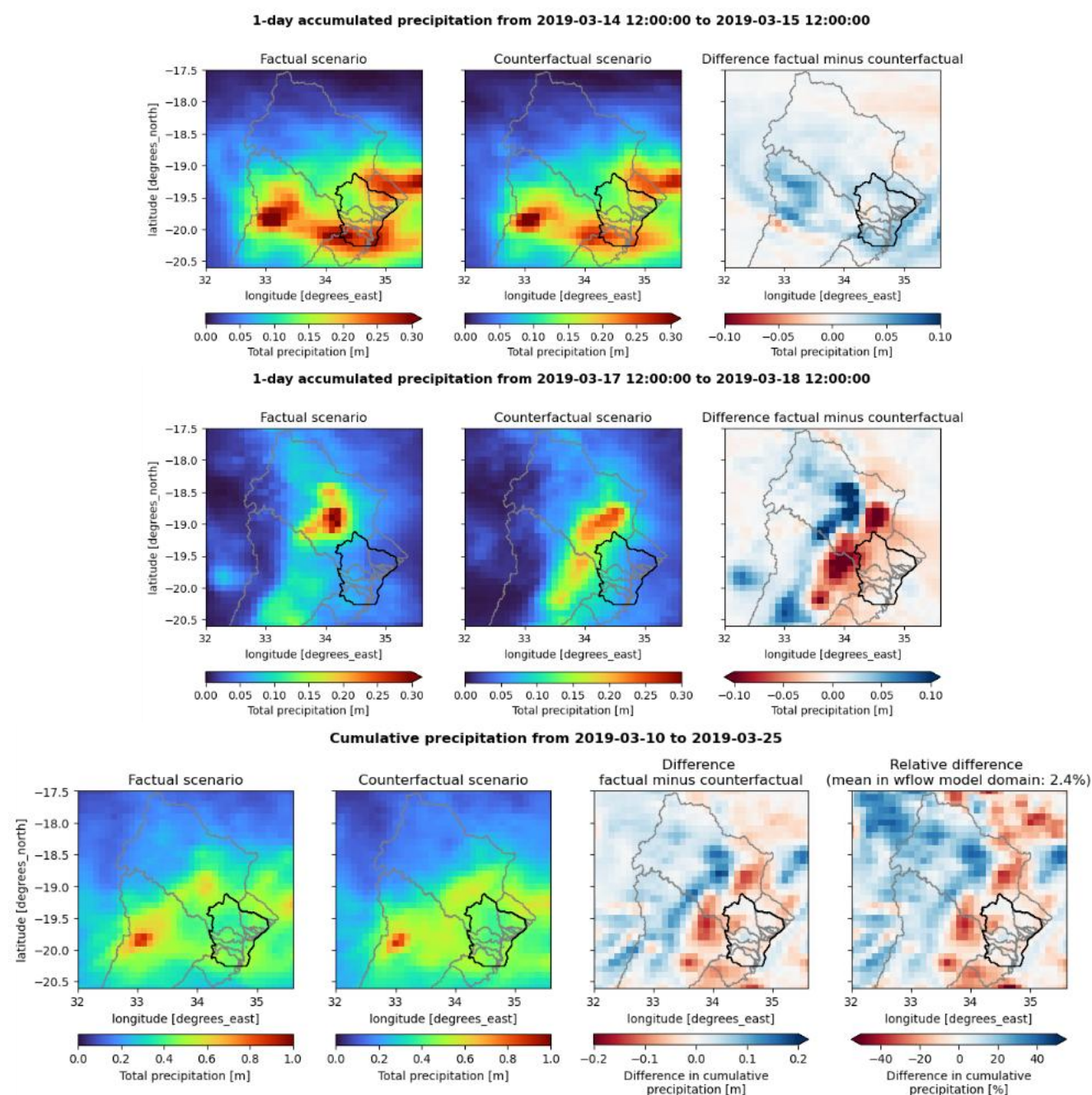


Figure 39: Spatial distribution of precipitation accumulated over a 24-hour period around the first precipitation peak at TC Idai landfall on 14-15 March (top), a 24-hour period around the second precipitation peak on 17-18 March (middle) and over the full model period of 10-25 March 2019 (bottom). Grey lines indicate the river catchments of the hydrological model (wflow), whereas the black outline indicates the flood model domain (SFINCS). Bottom right plot shows the relative difference in precipitation over the full event duration, calculated relative to the cumulative precipitation in the factual scenario.

In flood modelling, both the total aggregated rainfall over catchments and the spatial distribution of this rainfall are important, because different distribution of rainfall between and within catchments can lead to very different river discharges in the flood model. Based on the Phase 1 case study of TC Idai, it is known that upstream river discharges are a major driver of flooding in this study area. Hazard modelling in the next section shows how these changes in rainfall propagate to changes in flood extent and flood volume.

Precipitation comparison between ClimateDT factual scenario and ERA5 reanalysis

In Phase 1 use case for TC Idai we have used precipitation from the ERA5 reanalysis. Figure 40 shows a comparison between ClimateDT factual scenario and ERA5 precipitation. The spatial pattern and area-aggregated magnitude of precipitation during the first rainfall peak (14–15 March) is similar between ERA5 and ClimateDT, although in ClimateDT the rainfall is more concentrated (the grid resolution is also much finer at 9 km compared to 25 km for ERA5). However, for the second precipitation peak on 17–18 March, there is a significant difference both in area-aggregated precipitation volume and spatial distribution. Overall, in ERA5 most of the rainfall falls in the Buzi River catchment, whereas in the ClimateDT factual simulation the second rainfall peak is concentrated over the Pungwe catchment.

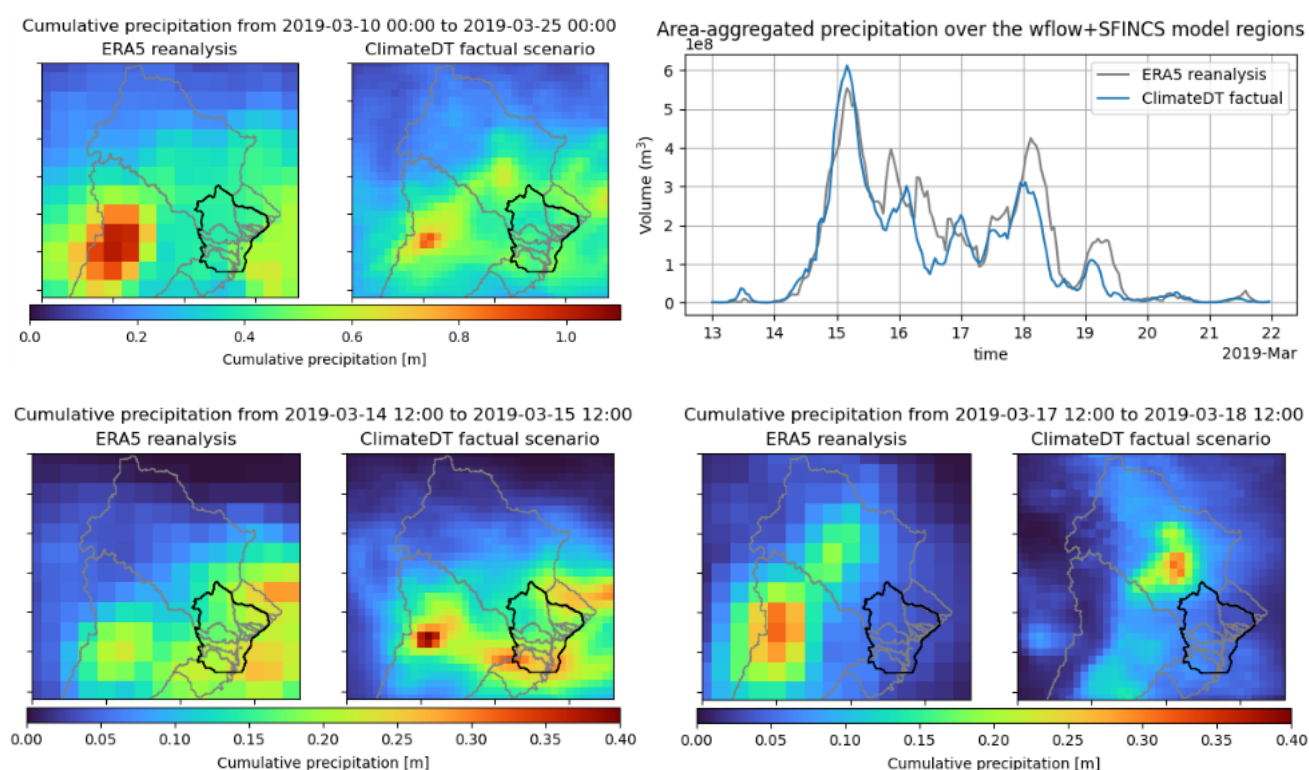


Figure 40: Comparison of precipitation in ERA5 and ClimateDT factual scenario for TC Idai over the model area. Grey lines indicate the river catchments of the hydrological model (wflow), black outline indicates the flood model domain (SFINCS).

5.3.2. Factual and counterfactual simulations

Compound flood hazard simulations were performed with ClimateDT storyline scenarios data as input. The modelling chain, consisting of the hydrological wmodel flow and flood model SFINCS, is almost the same as in the Phase 1 use case of TC Idai. In contrast with Phase I, coastal water levels are kept equal for the factual and counterfactual scenarios because the effect of climate change on wind and pressure is not modelled in nudged ClimateDT storylines. *Consequently, the attribution analysis of Phase II is focused on the effect of changes in the pluvial and fluvial flood drivers, conditioned on the unchanged coastal driver.*

The following variables are retrieved from the ClimateDT storylines dataset (at hourly temporal resolution and 9km spatial resolution) and are used in factual and counterfactual scenario modelling of flood hazard:

- Flood model (SFINCS): precipitation rate (tp), 10-m wind speeds (10v, 10u), mean sea level pressure (msl).
- Hydrological model (wflow): precipitation rate (tp), 2m air temperature (2t), incident shortwave radiation (tisir), surface shortwave radiation downwards (ssrd).

The results of the hydrological and flood models are summarized in Section 5.4.1.

5.4. Results

5.4.1. Hazard modelling results

The hydrological model *wflow* is used to determine river discharge boundary conditions for the flood model. Two main rivers are flowing into the model domain – the Buzi and Pungwe rivers. Figure 41 shows the river discharge timeseries for the factual and counterfactual scenarios based on ClimateDT storylines, and the precipitation volumes aggregated to the respective river catchment areas. For Buzi River catchment, the total precipitation volumes are similar between scenarios. Differences in the timing of the precipitation result in small differences in the river discharge timeseries, with larger peak discharge in the counterfactual scenario. For the Pungwe river, the differences are more significant: a much higher peak discharge is estimated in the factual scenario. At the same time, the difference in the precipitation volume is not as large, making it clear that changes in spatial and temporal distribution of precipitation within the catchment translate non-linearly to the river discharges.

The resulting maximum flood depths are compared in Figure 42. The differences in river discharges between the two scenarios are reflected in the differences in flood depths, with larger flood depths downstream of the Pungwe river inflow and smaller depths downstream of Buzi inflow. The net difference in flood extent and volume statistics reflects both larger extent and volume as derived from the maximum flood depth maps, and indicates an increase of approximately 5% in flood extent and 11% in volume in the factual scenario compared to counterfactual.

Comparing these results with the results from Phase I we can observe some differences. In the Phase I simulations a 8% reduction of rainfall led to an increase of 2% in the total flood extent, and a 9% increase in the total flood volume in the factual scenario compared to counterfactual. While the overall decrease in area-aggregated rainfall is smaller for the ClimateDT approach than the Clausius-Clapeyron approach used for Phase I (i.e. 4% vs. 8%), the results for the flood hazard show larger effects. This can be explained by the strong influence of spatial variability that is present in the ClimateDT storylines, whereas Clausius-Clapeyron was applied uniformly.

Table 6: Comparison of factual and counterfactual flood extent and volumes based on flood maps of maximum water levels during the flood simulation.

	ClimateDT storyline factual	ClimateDT storyline counterfactual	Difference
Flood extent (km ²)	3,520	3,350	+5%
Flood volume (M m ³)	5,097	4,583	+11%

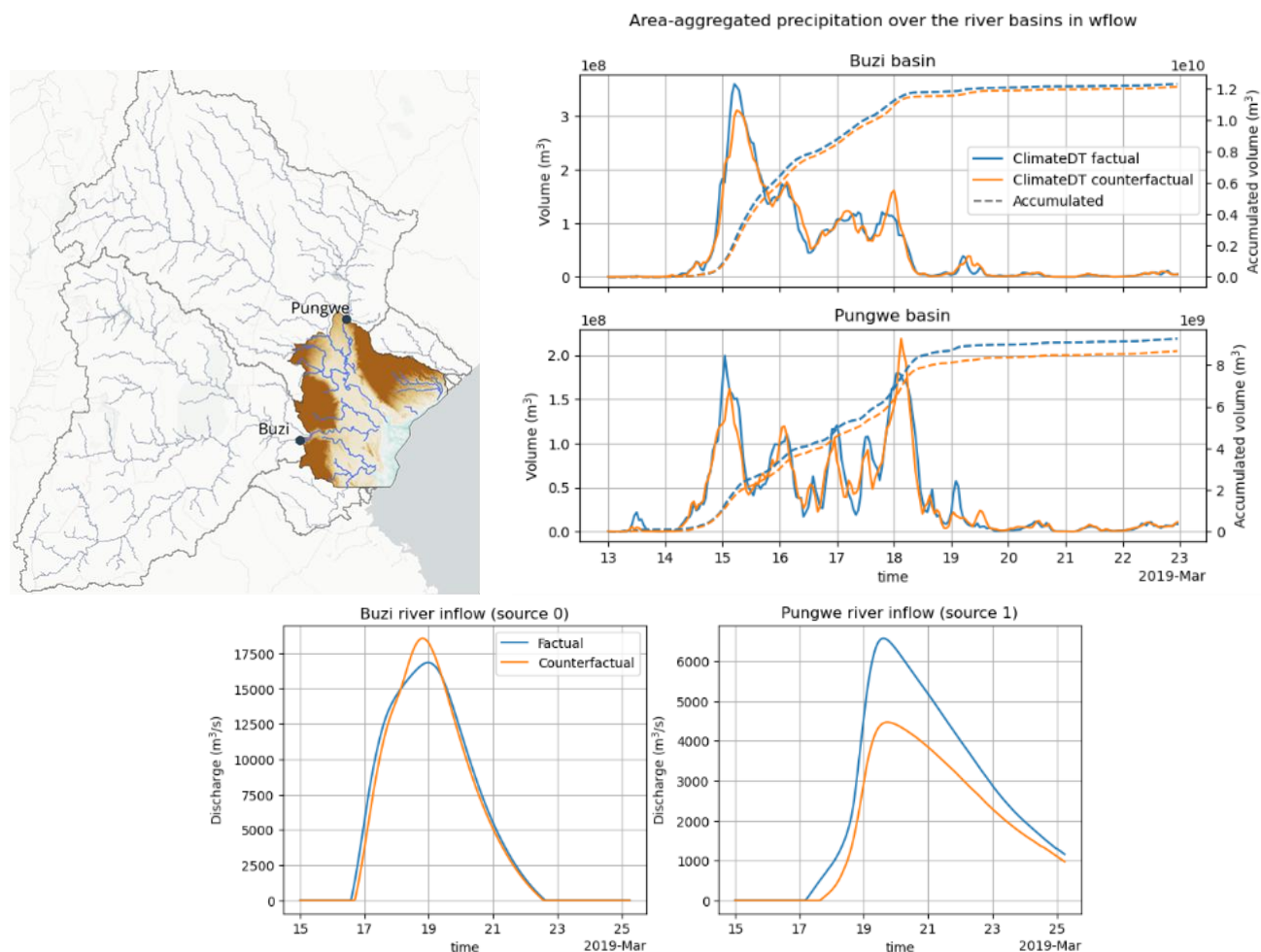


Figure 41: Comparison of precipitation volumes over the two main river basins and the corresponding river discharges generated using the hydrological model wflow for the factual and counterfactual scenarios of ClimateDT. Top left panel shows the outlines of the upstream river catchments and the location of the two river

inflows in the flood model domain (with the river network and topography elevation data shown in the background).

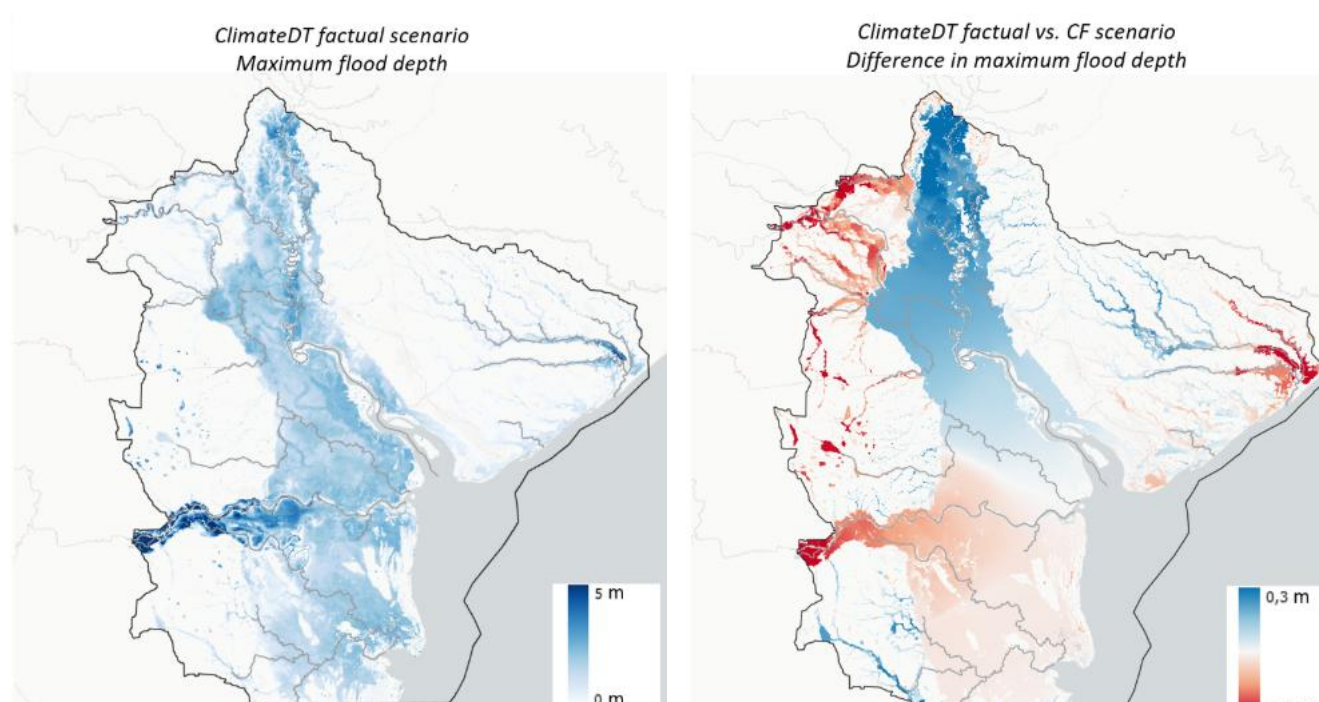


Figure 42: Flood modelling results based on the ClimateDT storylines meteorological forcing for TC Idai flooding in Sofala, Mozambique, model time period 10-25 March 2019.

The ClimateDT factual scenario can also be compared to the results previously obtained using ERA5 meteorological forcing. In Section 5.3.1, it was already shown that the precipitation magnitudes and patterns differ between the two datasets for the factual scenario. Figure 43 shows the results for river discharges and maximum flood depths based on the factual ClimateDT storyline and ERA5. Significant differences are found in the estimated discharges of Buzi River and, consequently, in the flood depths downstream of the Buzi inflow in the flood maps. This comparison highlights significant uncertainty in the meteorological products. This uncertainty in the representation of the factual event should be distinguished from uncertainty in the attribution signal itself, i.e. the difference between the ClimateDT factual and counterfactual simulations. However, despite this uncertainty, the comparison between the two ClimateDT storyline scenarios shown above provides useful insights into the non-linear response of the hydrological and flood modelling outputs to the changes in meteorological forcing under climate change.

Nudged storyline simulations can be influenced by a range of different model uncertainties. Based on a single set of factual and counterfactual precipitation fields it is not possible to determine to what extent the spatial differences described above are reflective of climate change and to what extent they are affected by model uncertainty. The spatial differences in precipitation mainly appear after the TC landfall, when wind speeds are drastically reduced. At lower wind speeds we can plausibly expect some spatial drift of the rainfall between different model realizations. To assess the effect of model uncertainty, an ensemble of storyline simulations is needed. Therefore, the estimated differences in flood extent (+5%) and flood volume (+11%) should not be interpreted as robust quantitative estimates of the climate-change contribution to TC Idai flooding. With only a single factual-counterfactual realization, it is not possible to determine whether the simulated spatial redistribution of precipitation represents a systematic climate-change signal or is partly associated with model variability.

A more robust assessment could be performed if ClimateDT storylines were available in multiple model realizations instead of a single deterministic dataset per scenario. This would allow us to assess which part of the difference in precipitation is associated with climate change, and which with model variability. Overall, the relatively small scale of the modelled area (compared to the TC radius) means that the model results are very sensitive to the spatial and temporal distribution of precipitation.

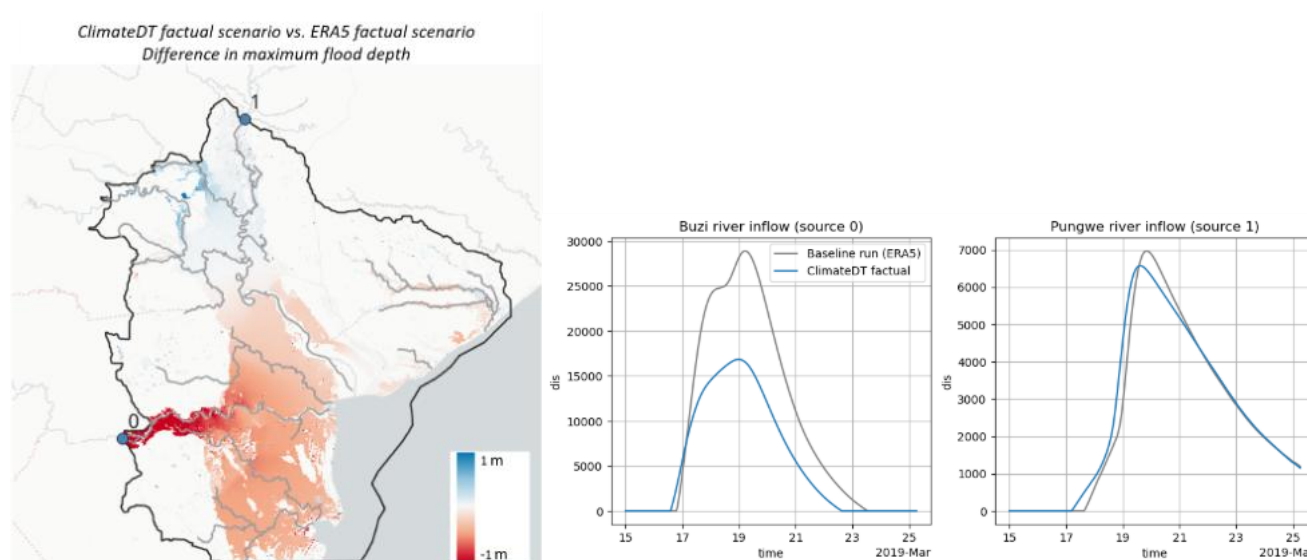


Figure 43: Difference in modelled river discharge and maximum flood depth between the ClimateDT factual scenario and ERA5 factual scenario flood simulations for TC Idai flooding in Sofala, Mozambique, model time period 10-25 March 2019.

5.4.2. Stakeholder and policy relevance

Stakeholder engagement workshops

Compared to Phase I use case of TC Idai, which included key informant interviews, no additional stakeholder engagement took place. The hazard and attribution results based on the ClimateDT provide new insights of how physically consistent climate storylines can be derived and used for subsequent analysis. It shows that there is a climate signal but also considerable uncertainty and non-linear effects of climate change on flooding. As such, it is important to realize that the flood response to climate change is complex and non-linear. The results also highlight that flood-risk assessments should consider changes in the spatial and temporal distribution of extreme precipitation, rather than relying only on changes in event-total or area-averaged precipitation. The main focus of the use case was on the flood hazard modelling, while the modelling of impacts was outside the scope. Extending the approach to include impacts would increase the policy relevance.

Dissemination

In terms of dissemination, a publication based on the ClimateDT storyline simulations is in preparation. The use case of TC Idai forms the basis of several scientific publications:

- Vertegaal, D. M., van den Hurk, B. J. J. M., Couasnon, A., Aleksandrova, N., Bovenschen, T., Gradiyanto, F., Leijnse, T. W. B., Goulart, H. M. D., and Muis, S.: Climate and impact attribution of compound flooding induced by tropical cyclone Idai in Mozambique, *Nat. Hazards Earth Syst. Sci.*, 26, 1417–1433, <https://doi.org/10.5194/nhess-26-1417-2026>, 2026.
- Webb, P. E., Vertegaal, D., Vogel, M. M., Jack, C. D., and 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, *EGUsphere* [preprint], <https://doi.org/10.5194/egusphere-2026-2454>, 2026.

- Vertegaal, D. M., van den Hurk, B. J. J. M., Couasnon, A., Paprotny, D., and Muis, S.: Impact attribution of climate and population change on compound flood impacts from tropical cyclone Idai in Mozambique, 2026. In Review.

The work was also presented at several conferences, including at the [European Geosciences Union](#) and at the [European Meteorological Society](#).

6. Use case 4: Tropical storms Eta and Iota (2020) extended

6.1. Summary of findings phase 1

The Phase I analysis of Tropical Storms Eta and Iota examined the hazards and impacts associated with two successive tropical cyclones that made landfall on the 4th and 17th November respectively, significantly affecting Honduras. The events produced extreme rainfall and widespread flooding, with the impacts influenced by antecedent rainfall, hydrological conditions, exposure, and underlying vulnerability. The modelling framework combined rainfall forcing with hydrological and hydrodynamic modelling to reproduce the resulting river discharge and flood dynamics. The attribution framework explored the contribution of climatic and non-climatic drivers, including changes in precipitation intensity and the sequential occurrence of the two storms. Causal mapping informed by document analysis and stakeholder engagement identified important socio-economic drivers of vulnerability and risk, including chronic insecurity, Covid-19 pandemic impacts, and internal displacement. The results highlighted the important role of pre-existing hydrological and socio-economic conditions and the complexity of attributing impacts in successive events, while also demonstrating the need to better quantify the relative contributions of climate change and other drivers to the observed impacts.

The use case highlighted challenges in the hydrological and flood modeling potentially related to the resolution of the topography and land use data. The result was a very limited — and in some cases counter-intuitive — impact of rainfall intensity changes on flood extent and depth, which resulted in no observable contribution of climate change to flooding despite a prescribed change in rainfall intensity (based on Clausius-Clapeyron assumption).

6.2. Objective of extension

The objective of this extension is to improve the representation of the hydrological and flood processes associated with the successive impacts of Tropical Storms Eta and Iota, thereby strengthening the attribution of the resulting flood impacts. The extension incorporates improvements in the representation of topography, river channels, land cover, and surface roughness, while also optimizing the domains of the hydrological and hydrodynamic models. These enhancements aim to provide a more accurate simulation of the observed flooding and to reduce uncertainties in the assessment of climate and non-climate counterfactual scenarios. In particular, the extension seeks to better quantify the respective contributions of changes in precipitation intensity, the sequential occurrence of Eta and Iota, and land-use conditions to the magnitude and spatial distribution of the resulting flood impacts.

6.3. Updated (attribution) modeling framework

The hazard modeling framework applied to the Eta and Iota in the Sula Valley (Cortés, Honduras) follows the same methodology as in Phase 1, with several improvements to increase the accuracy of the hazard modelling in this region (cf. Deliverable 4.1 for Phase 1, and Deliverable 1.1. for the details on the modelling framework). The modifications have been selected after an evaluation of the Phase 1 flood modelling results revealing the need for a more accurate modelling of the counterfactual scenarios. The improvements are described below.

Topography data and grid resolution

Topography data is sourced from Forest and Buildings removed Copernicus Digital Elevation Model (FABDEM)⁷⁴, and the flood model grid resolution is refined to 60m grid cell size with 15m subgrid cell size. This allows for an improved representation of narrow river channels in the upstream part of the model, ensuring more realistic hydraulic connectivity.

Model domain

⁷⁴ Hawker, L., & Neal, J. (2022). *A 30 m global map of elevation with forests and buildings removed*. Environmental Research Letters. <https://doi.org/10.1088/1748-9326/ac4d4f>

The model domain in both the hydrological (wflow) and hydrodynamic flood model (SFINCS) was optimized to only include the catchments that flow into the Sula Valley, removing unnecessary computations. Figure shows the extent of the two models and the terrain of the flood model.

Land cover and surface roughness

Land cover maps used in defining the land surface roughness have been updated with the latest land use map from Copernicus Land Monitoring Service, offering 10m resolution for land use for 2020⁷⁵ (instead of the 100 m map for 2019, which was used previously⁷⁶). This finer resolution of the land use map is especially helpful for improving the definition of surface roughness on and around the river channels (many of these river channels are only ~100m wide in the upstream part of the area of interest). The difference in resolution is shown in Figure . This figure also shows striking differences between the two land cover dataset versions: in the new 10m land cover dataset, the agriculture (cropland, cultivated land) zones are a lot smaller than in the previously used 100m version. Many zones previously identified as cropland are now identified as grassland or forest. This difference highlights the uncertainty associated with global satellite-derived land cover products, and this uncertainty is also reflected in the flood modelling results (see Section 6.3.4 on land cover counterfactuals).

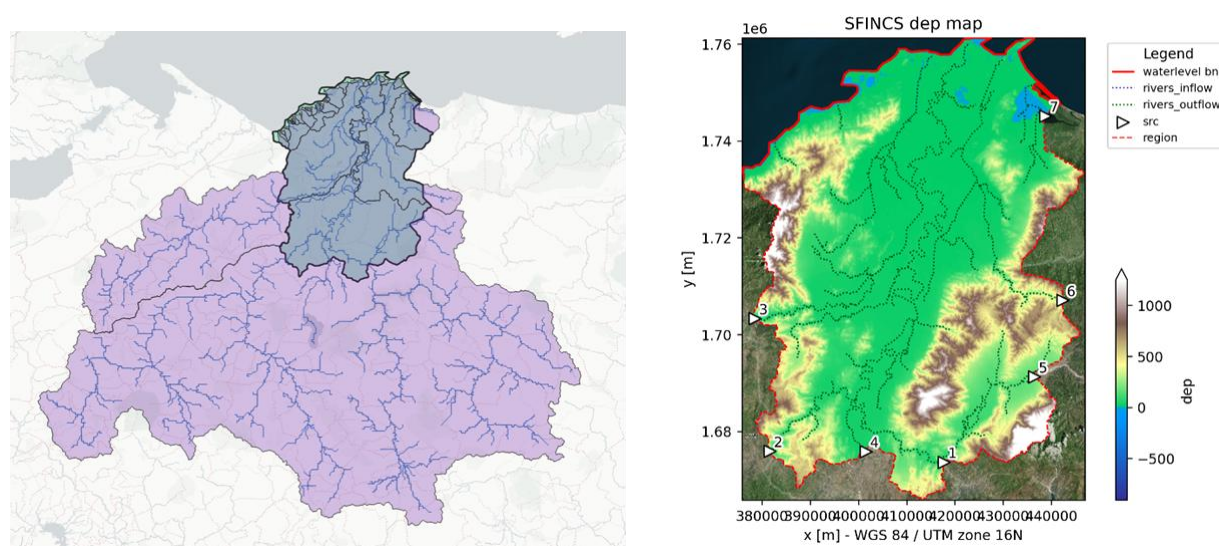


Figure 44: Spatial extent of the flood model (blue) and hydrological model (pink) (left); topography map of the SFINCS flood model with river inflow points indicated with white triangles (right).

⁷⁵ Copernicus Land Monitoring Service. *Land Cover 2020 (raster 10 m), global, annual – version 1*. DOI: <https://doi.org/10.2909/602507b2-96c7-47bb-b79d-7ba25e97d0a9>

⁷⁶ Copernicus Land Monitoring Service. *Land Cover 2015-2019 (raster 100 m), global, yearly – version 3*. DOI: <https://doi.org/10.2909/c6377c6e-76cc-4d03-8330-628a03693042>

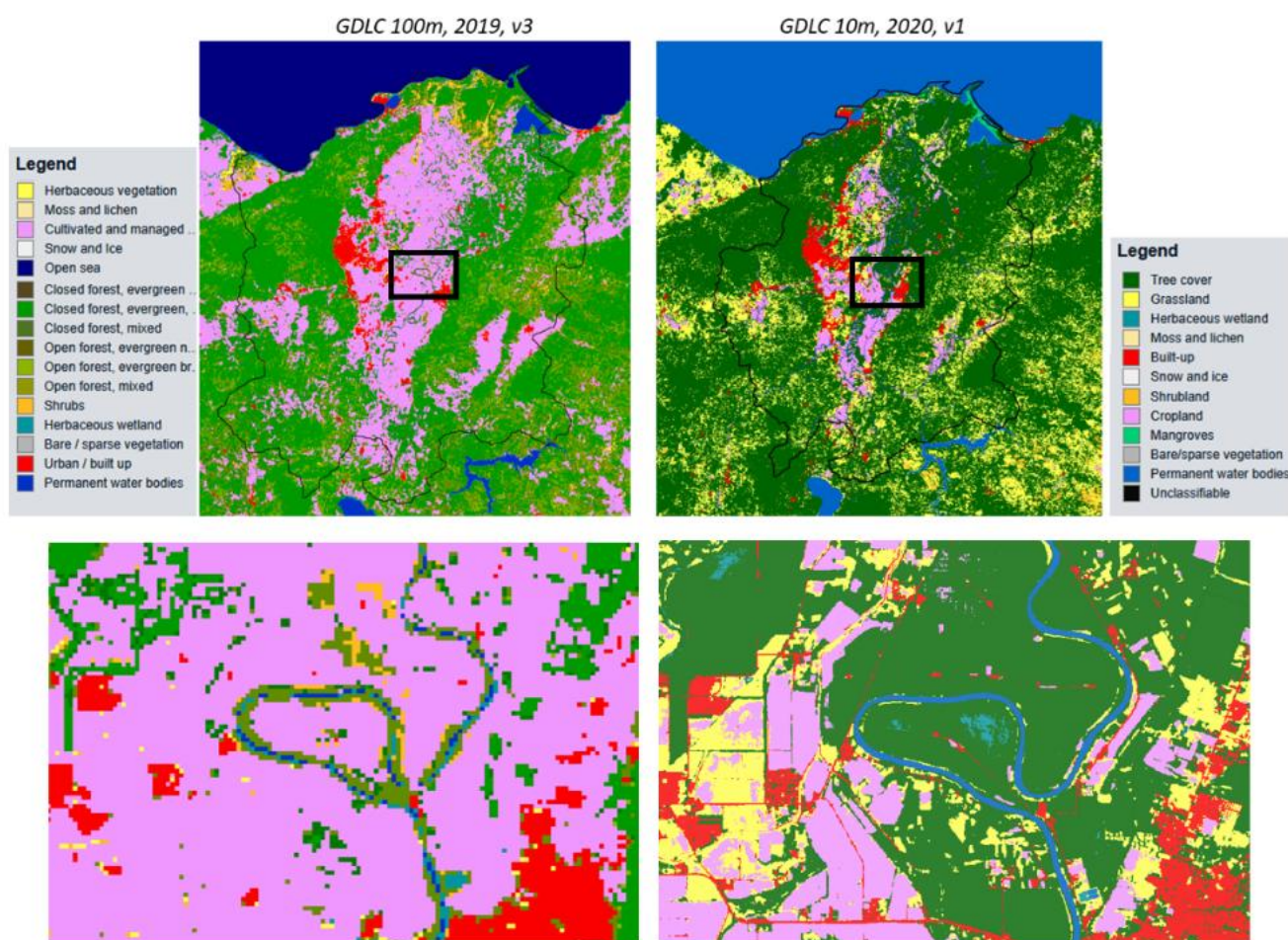


Figure 45: Land cover datasets comparison between Global Dynamic Land Cover 100m, 2019 (left) and 10m, 2020 (right) versions. Land cover maps for the full extent of the flood model (top panel), and detail enlargements demonstrating the difference in resolution (bottom panel).

6.3.1. Updated factual simulation

The factual simulation for TC Eta and Iota is performed by running the hazard modelling workflow with ERA5 precipitation forcing for the period 1-27 November 2020. Figure illustrates precipitation forcing used in the models. Two clear precipitation peaks are visible: first peak on 4 November (TC Eta) and second (larger) peak on 18-19 November (TC Iota). In both cases, most of the rainfall accumulates on the west side of the model domains, over the catchments of Rio Chamelecon and Rio Ulua.

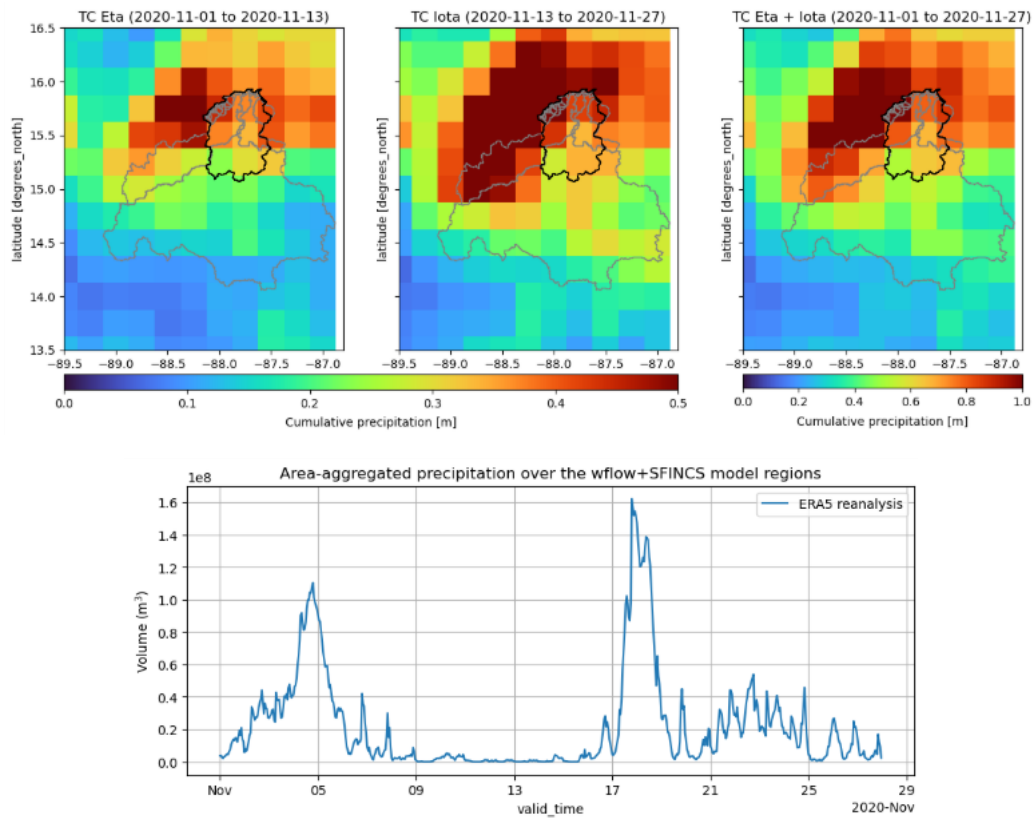


Figure 46: Precipitation over the modelling area during TC Eta and Iota (2020).

Precipitation over the upstream river catchments is translated to river discharge using the hydrological model wflow, which is then fed into the flood model via 7 inflow points, see Figure for their locations. Figure shows the timeseries of river discharges for the 5 largest discharges. This figure shows that the largest discharges come from Rio Sulaco (source 1), Rio Ulua (source 2), and Rio Chamelecon (source 3). During TC Iota the discharge of Rio Ulua is especially extreme, peaking at more than 10000 m³/s.

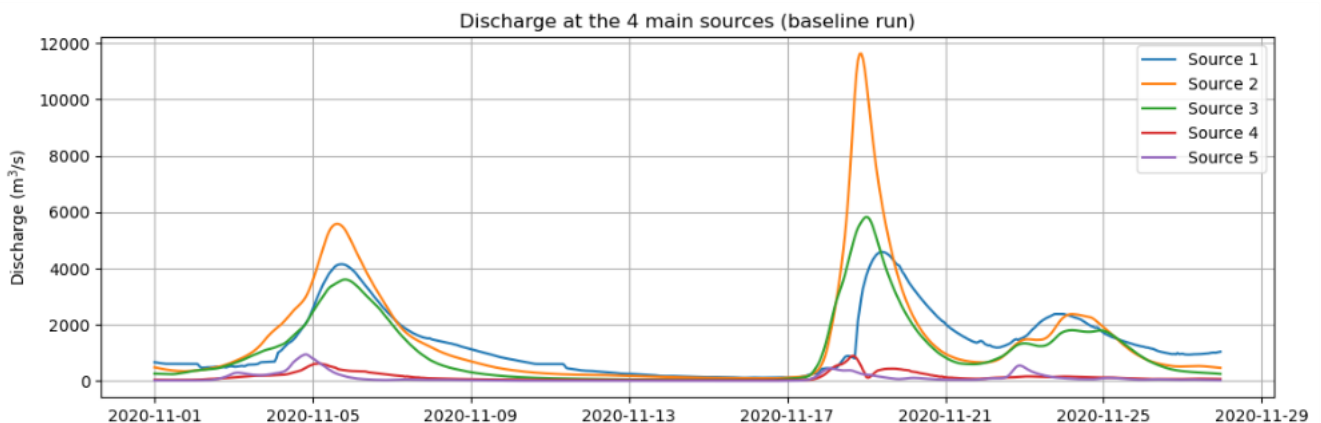


Figure 47: River discharge timeseries derived from the hydrological model and used as a boundary condition in the flood model. The numbering of river inflow points corresponds to the numbering in Figure (right). TC Eta and Iota made landfall on the 4th and 17th November, respectively.

The combination of these river discharges and local precipitation, as they propagate within the domain of the hydrodynamic flood model, results in downstream flooding of the valley. Coastal water levels are supplied to

the model based on GTSM-ERA5 reanalysis⁷⁷. The coastal water levels do not show any significant elevation due to the storm and are not a driver of flooding in this case study; therefore, the global GTSM-ERA5 dataset is deemed sufficient to supply the coastal boundary conditions for the compound flood modeling.

The flood model results for the factual simulation of TC Eta and Iota are validated against satellite-derived flood maps, which are available via UNOSAT^{78,79} and mapped by NOAA based on Sentinel-1 observations. Figure shows the comparison between modelled and satellite-derived flood maps. Generally, the model captures the extent of the flooding reasonably well (indicated as true positives in blue), with ‘overprediction’ in a number of areas (false positive, red). It should be noted that both the flooding modelling and satellite-derived flood maps carry a degree of uncertainty. For example, flooding in densely forested areas is harder to detect using the satellites, which is likely the reason for the lack of flooding in the satellite-derived map in the large coastal area indicated in red in the figure, where a dense forest is located (El Tigre, Atlántida region). Sentinel data limitations originate from the irregular and relatively infrequent timing of satellite overpass, which means that maximum flood extent can occur between satellite image acquisition dates. Image processing can also create spurious water body detection resulting from changing shadows in mountain regions and other sources of noise. Moreover, there is also considerable uncertainty in the input datasets (ERA5 rainfall, elevations, etc), which could contribute to the differences as well.

⁷⁷ Muis, S., Aerts, J. C. J. H., Á. Antolínez, J. A., Dullaart, J. C., Duong, T. M., Erikson, L., et al. (2023). *Global projections of storm surges using high-resolution CMIP6 climate models*. *Earth's Future*, 11, e2023EF003479. <https://doi.org/10.1029/2023EF003479>

⁷⁸ UNITAR-UNOSAT (2020). *Satellite detected water extents between 13 & 17 November 2020 in Honduras*. Product ID:2910. Available at: <https://unosat.org/products/>

⁷⁹ UNITAR-UNOSAT (2020). *Satellite detected waters in Cortes, Atlantida, and Yoro departments of Honduras as of 25 November 2020*. Product ID: 2990. Available at: <https://unosat.org/products/>

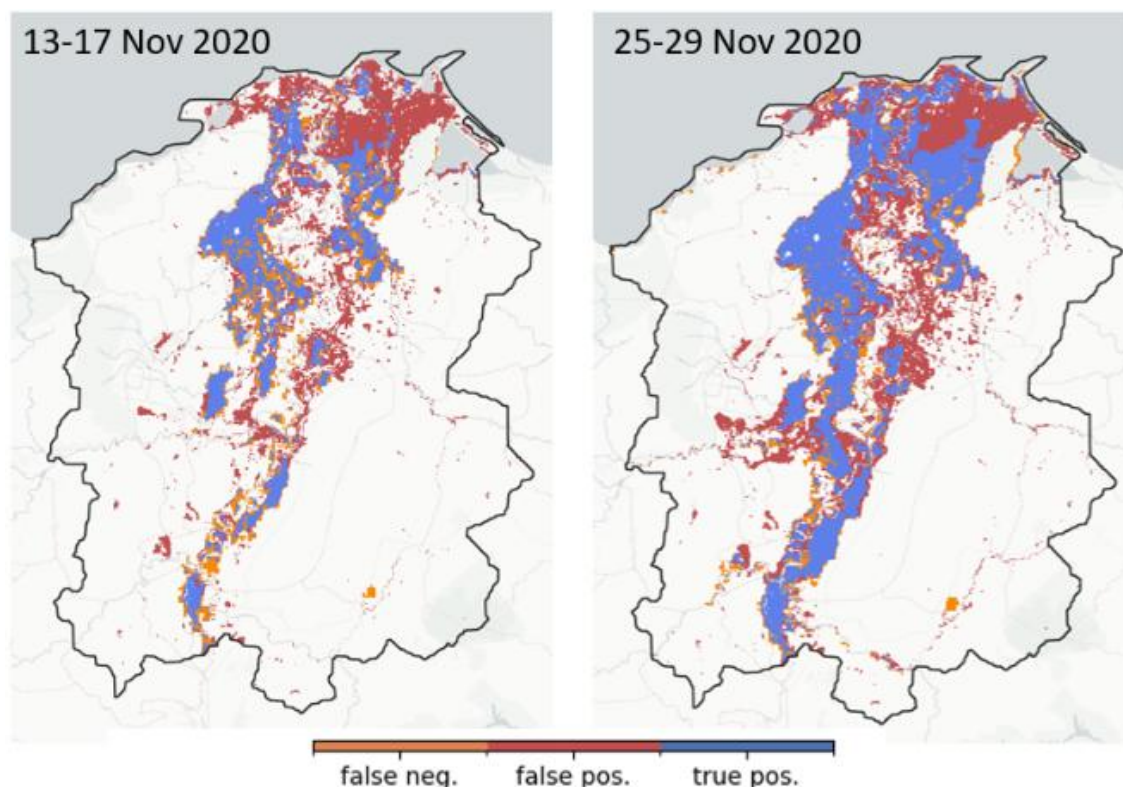


Figure 48: Flood extent validation comparing flood model results to satellite-derived flood maps (UNOSAT, derived by NOAA based on Sentinel-1 images) for Eta (left) and Iota (right).

6.3.2. Counterfactual simulations

Climate-counterfactuals

As in Phase I, the climate-counterfactual simulating a 1.2°C colder climate was constructed by reducing the precipitation intensity by 9%, approximating the change in rainfall intensity according to the Clausius-Clapeyron relation ($\sim +7\%$ increase per degree of warming). This counterfactual rainfall timeseries were used to drive both the hydrological model (for river discharges) and flood model (as local rainfall). Figure shows the differences in forcing and maximum flood depth.

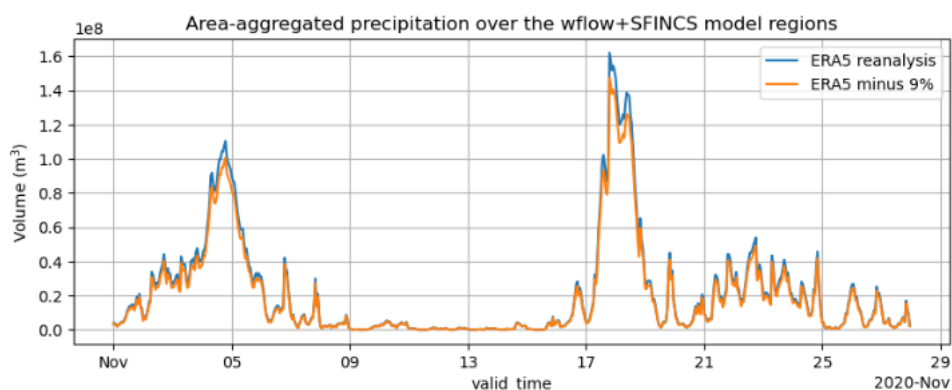


Figure 49: Factual (blue) and counterfactual (orange) area-aggregated precipitation time series for Eta and Iota. The factual precipitation is represented by the ERA5 reanalysis, while the counterfactual precipitation is represented by ERA5 precipitation reduced by 9%. Precipitation is aggregated over the wflow+SFINCS model regions. The time series covers November 2020, including the periods of Hurricanes Eta and Iota.

Deforestation counterfactual

Stakeholder engagements and document analysis in Phase 1 identified deforestation as a potential non-climate driver of increased flood intensity for Eta and Iota. In this phase, a deforestation counterfactual was created in order to explore this effect. Deforestation was identified using a land-use change dataset⁸⁰. This dataset assessed changes in land cover derived from Landsat imagery between 2000 and 2012 and results in estimates of deforested area year by year through this period at 30m resolution. The deforestation dataset was regridded to match the GDLC spatial grid at 10m (nearest neighbour method) and 100m (area averaging). Grid points marked as undergoing deforestation through this period were then used to change the corresponding GDLC grid points back to tree cover if they weren't already some form of tree cover. Multiple types of tree cover are represented in GDLC at 100m. The reversion to tree cover used the dominant closed forest broadleaf category of the region, as no other information was available on original (pre-deforestation) tree cover.

It is important to note that this counterfactual only adjusted land-use classification and did not represent other influences of deforestation such as soil depth which would influence infiltration. The hydrological model translates land-cover types into estimates of roughness length so essentially this counter-factual is equivalent to a roughness length counter-factual associated with deforestation.

6.4. Results

6.4.1. Factual of flood hazard

Building on the updated model configuration described in Section 6.3, the factual flood simulation was evaluated separately for TC Eta and TC Iota, as well as the combined comparison shown in Figure . The modeled flood extent for each event was compared against NOAA's satellite-derived flood maps, produced from Sentinel-1 imagery and distributed via UNOSAT, covering November 13-17, 2020, for TC Eta and November 25-29, 2020, for TC Iota (see **Error! Reference source not found.**). Sentinel-1 satellite data analysis enables mapping of water body extent, and flood extent can be derived by differentiating pre-flood water body extent from water body extent during flooding. Sentinel flood extent analysis was obtained from the Copernicus EMS Rapid Mapping service, which provides flood mapping data for significant flood events in support of emergency response and recovery.

For both events, the updated model reproduces the general spatial pattern of observed flooding across the Sula Valley, with the largest and most extensive inundation associated with TC Iota, consistent with its larger and more widespread rainfall totals compared with TC Eta (Figure). As in the combined comparison (Figure), some overprediction is evident for both events, and the comparison remains affected by known limitations of the satellite-derived reference data, particularly the reduced detectability of flooding beneath dense forest canopy.

Observed flood extent and impact

Figure shows an estimate of the maximum flood extent and population exposed based on Sentinel satellite data. Limitations include the irregular and relatively infrequent timing of satellite overpass which means that maximum flood extent can occur between satellite image acquisition dates. Image processing can also create spurious water body detection resulting from changing shadows in mountain regions and other sources of noise. Results indicate a total of 66,498 people exposed to flooding in the region.

⁸⁰ Hansen, M. C., Potapov, P. V., Moore, R., Hancher, M., Turubanova, S. A., Tyukavina, A., ... & Townshend, J. R. (2013). *High-resolution global maps of 21st-century forest cover change*. Science, 342(6160), 850-853.

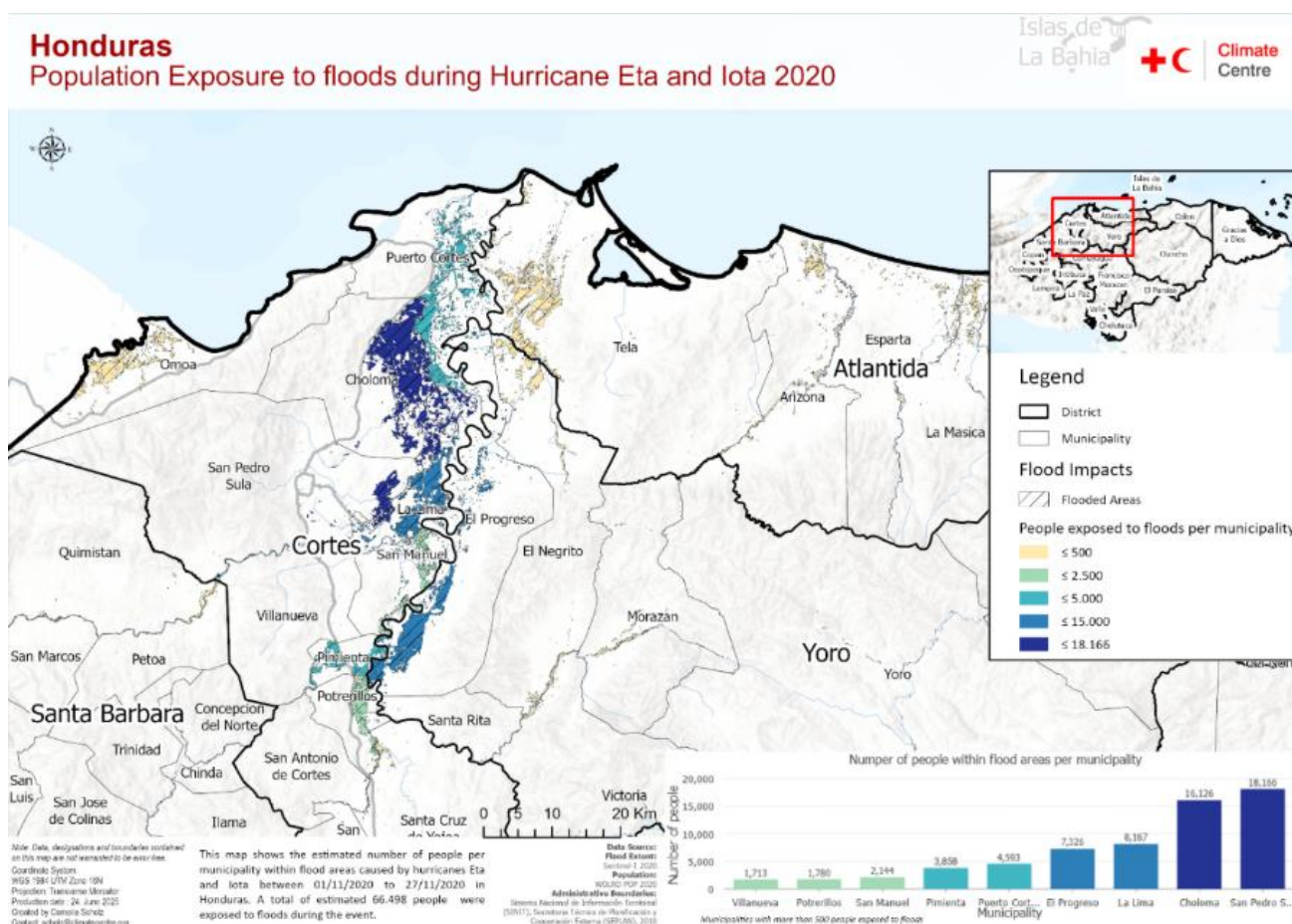


Figure 50: Population exposure to floods during Hurricane Eta and Iota 2020 – Sentinel 1 flood analysis 2020; Map – Climate Centre 2025.

Figure assesses the building exposure to provide an indication of the number of buildings potentially flooded, which is strongly associated with displacement of populations to temporary accommodation.

Estimates of population and buildings exposed to flooding through the Sentinel-based mapping are much lower than reported figures. Total population exposed, based on Copernicus mapping, is 66,498, and buildings exposed are 2,543, whereas the reported number of people evacuated was 437,000 and homes affected were 90,000. It is plausible that the Sentinel-based flood mapping underestimates the number of exposed people due to some of the limitations described above, in particular the satellite image acquisition timing relative to the timing of the peak flood extent. Simulated flood extents under a factual scenario (see below) result in people and buildings affected that align far better with reported impacts, suggesting that observed flood extent may be significantly underestimated. However, it is also very likely that many people were evacuated even if their homes were not flooded. These two factors combined could explain some of the discrepancy between reported impacts and the Sentinel-based mapping analysis.

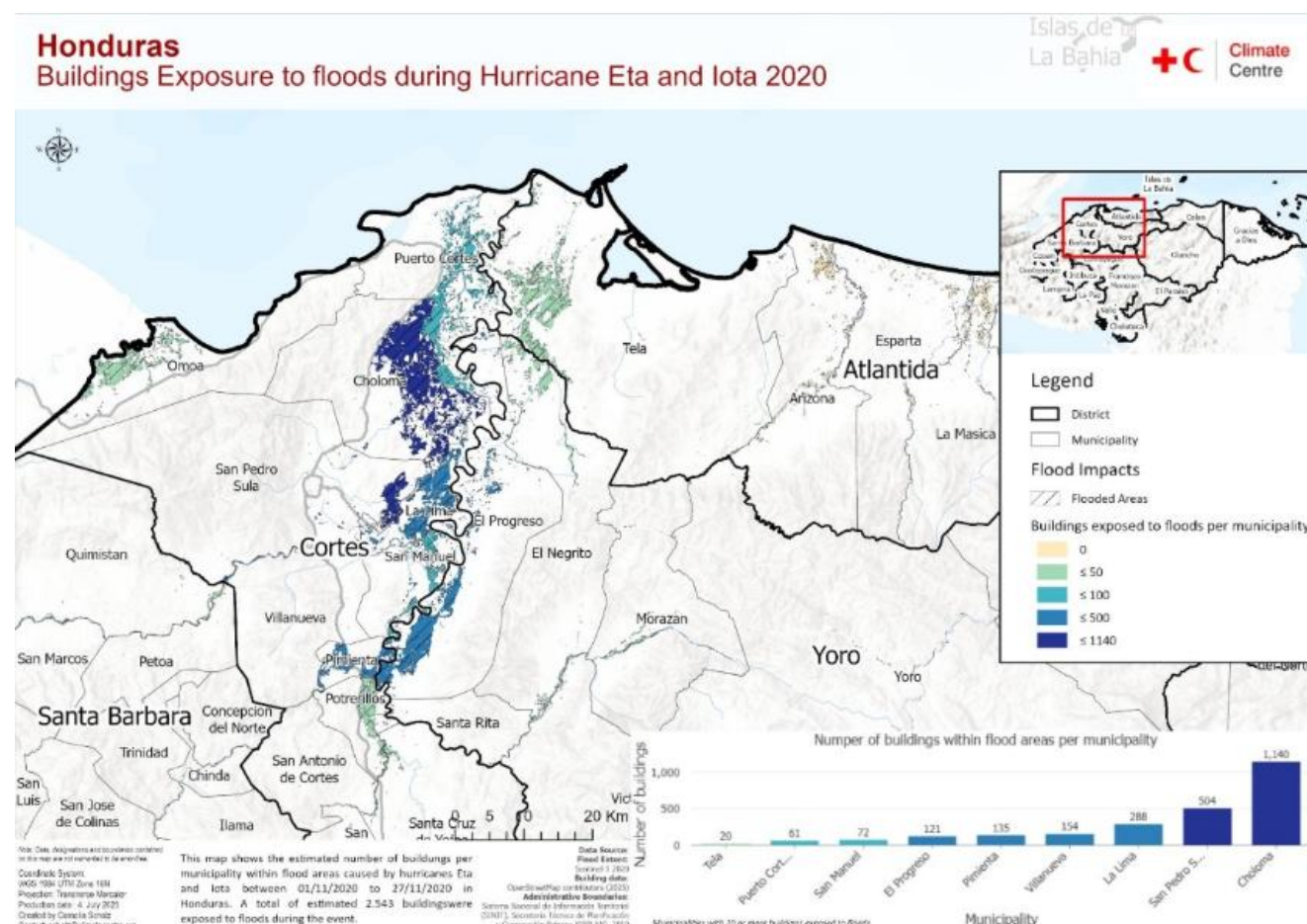


Figure 51: Population exposure to floods during Hurricane Eta and Iota 2020 – Sentinel 1 flood analysis 2020; Map – Climate Centre. The map shows the estimated number of buildings per municipality with flood areas caused by hurricones ETA and Iota. A total of estimated 2,543 buildings were exposed to floods during the event.

6.4.2. Attribution results

The climate counterfactual, which assumes a uniform 9% decrease in precipitation intensity based on the Clausius-Clapeyron scaling (Section 6.3.2), was applied consistently to both the hydrological and hydrodynamic parts of the model chain. Comparing the actual and counterfactual runs over the combined TC Eta-Iota period (Figure) reveals that the higher precipitation intensity in the actual scenario results in increased river discharges, most notably for Rio Ulua and Rio Chamelecon, and larger maximum flood depths across the Sula Valley. This aligns with an amplifying effect of climate change on rainfall-driven flooding in this region.

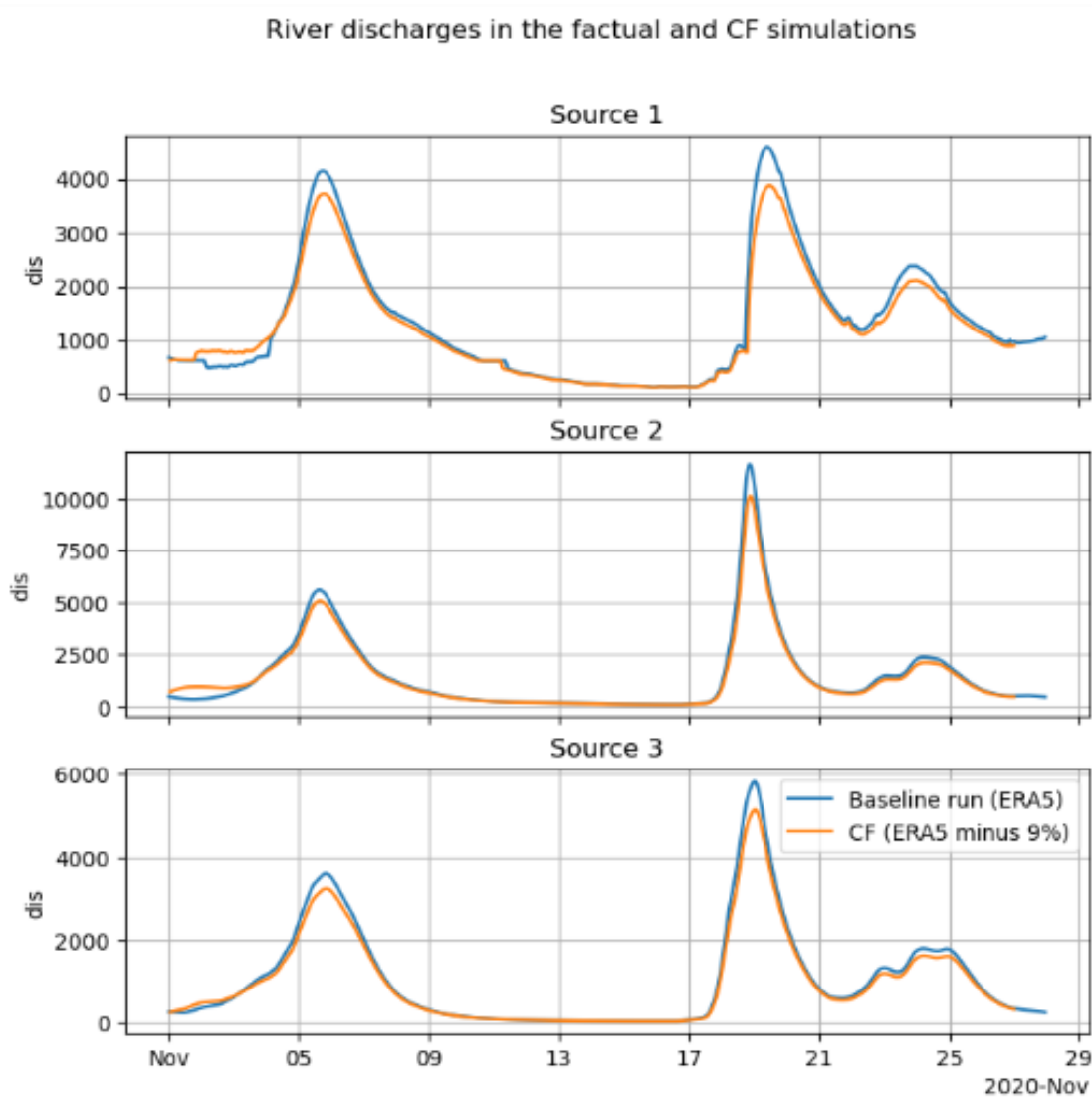


Figure 52: Factual and counter-factual river discharge time series (dis) in m^3/s obtained from hydrological modelling for the 3 main sources Chulaco (Source 1), Ulua (Source 2) and Chamelecon (Source 3). The counterfactual (CF) run reduces ERA5 precipitation by 9%.

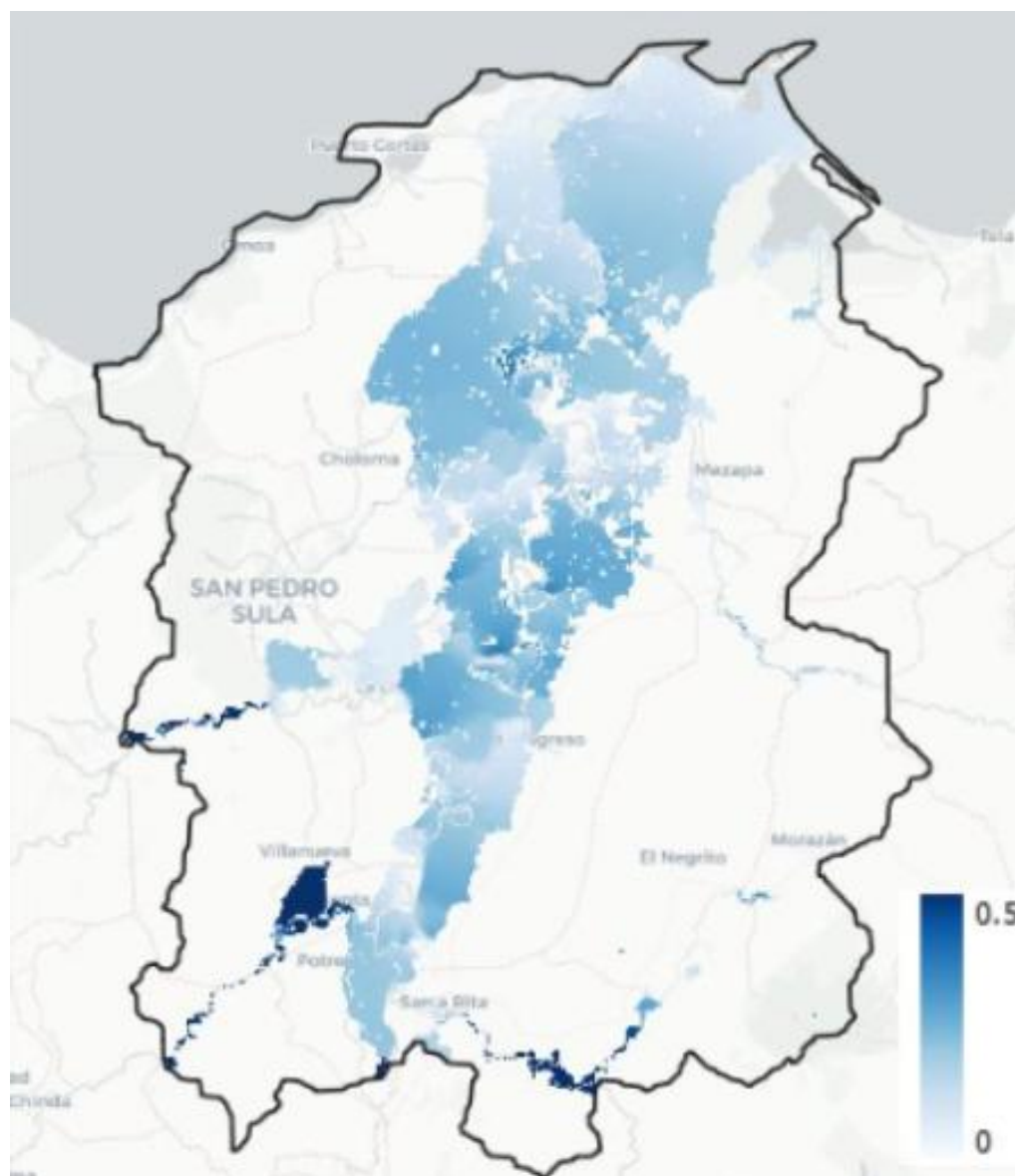


Figure 53: Maximum flood depth difference in m (factual minus counterfactual). The black boundary shows the extent of the hydrodynamic flood model, see Figure .

Deforestation counter-factuals

For both land-use resolutions (100m and 10m), the factual scenario with more deforestation has lower surface roughness in the Sula Valley compared to the counterfactual with more forest, causing water to flow faster downstream and resulting in lower maximum flood depths (see Figure). River discharges from the hydrological model remain nearly unchanged by land-use scenario, as the model mainly considers land cover's effect on surface roughness, not infiltration or rooting depth. The magnitude of this non-climate effect varies between datasets: the 100m dataset shows a larger difference in flood depth because it assigns more cropland to the counterfactual, whereas the 10m dataset shows a smaller, more localized difference mainly driven by roughness changes. This highlights the uncertainty from different land cover products and reveals a limitation of the current model: land-use change is only represented via surface roughness, excluding other effects such as infiltration, interception, evapotranspiration, or erosion that also influence flooding after deforestation. Due to the minimal changes in flood depth, impact differences (population and building exposure) were not assessed for this counterfactual.

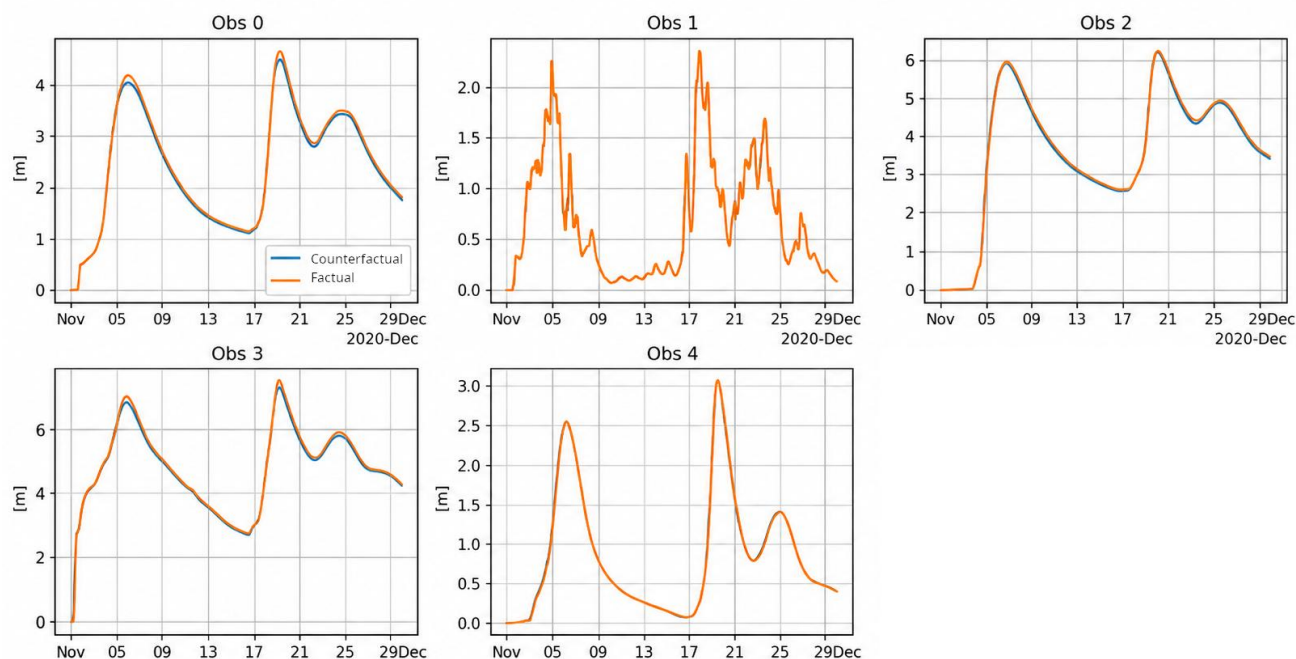


Figure 54: Factual Flood depth simulations for the land-use (deforestation) factual and counterfactual, based on the 10m Global Dynamic Land Cover dataset for selected pseudo-observation points across the domain.

Exposure counter-factuals

Figure 55 and Figure 56 assess population and building exposure to flood extent under the factual scenario, respectively. Results indicate that in total 630,827 people and 133,916 buildings were exposed to flooding by Eta and Iota. These results differ significantly from the estimates based on satellite imagery (66,498 people and 2,543 buildings) but are closer to reported impacts of people evacuated (437,000) and homes affected (90,000)

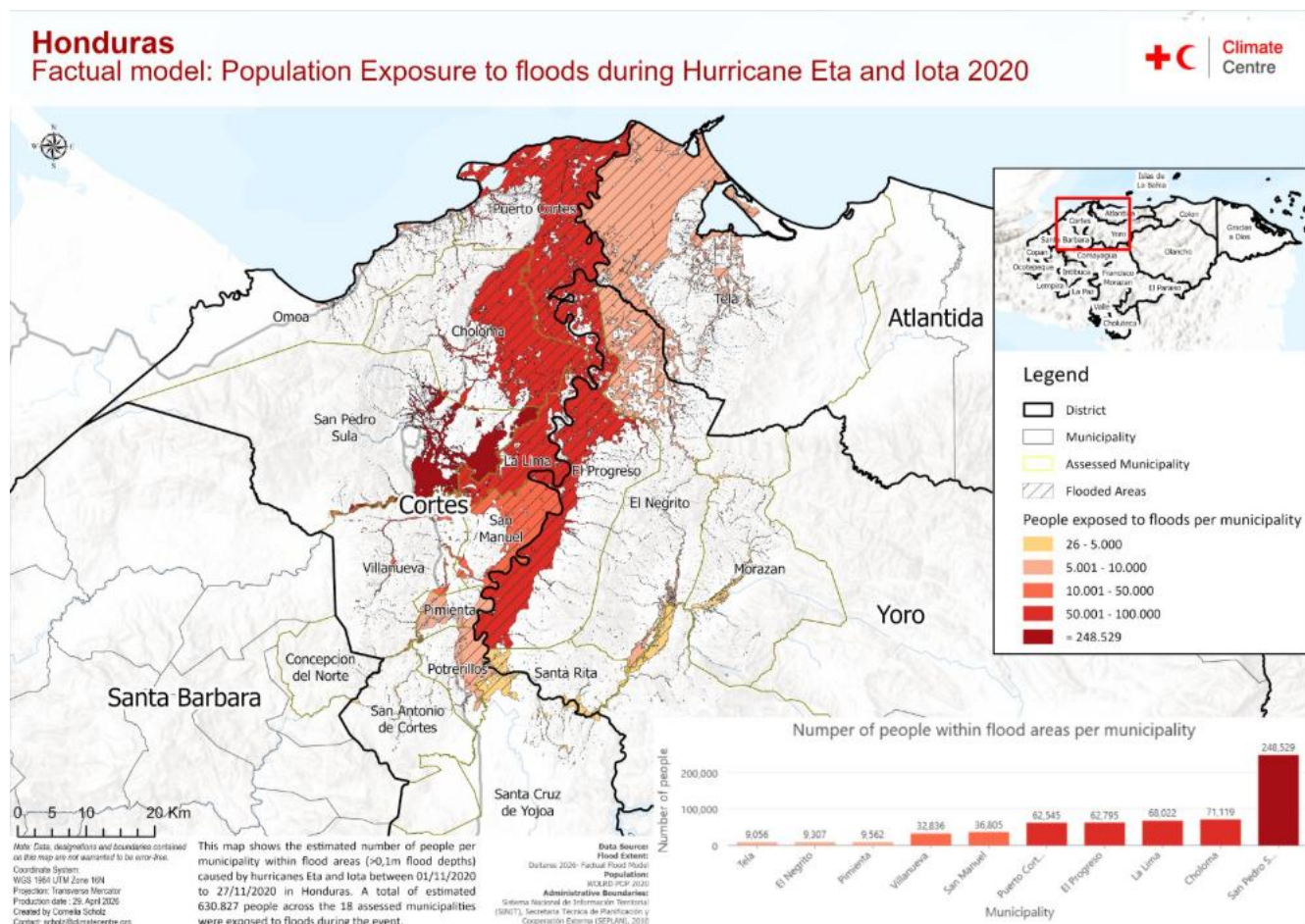


Figure 55: Population exposure to flooding under factual scenario

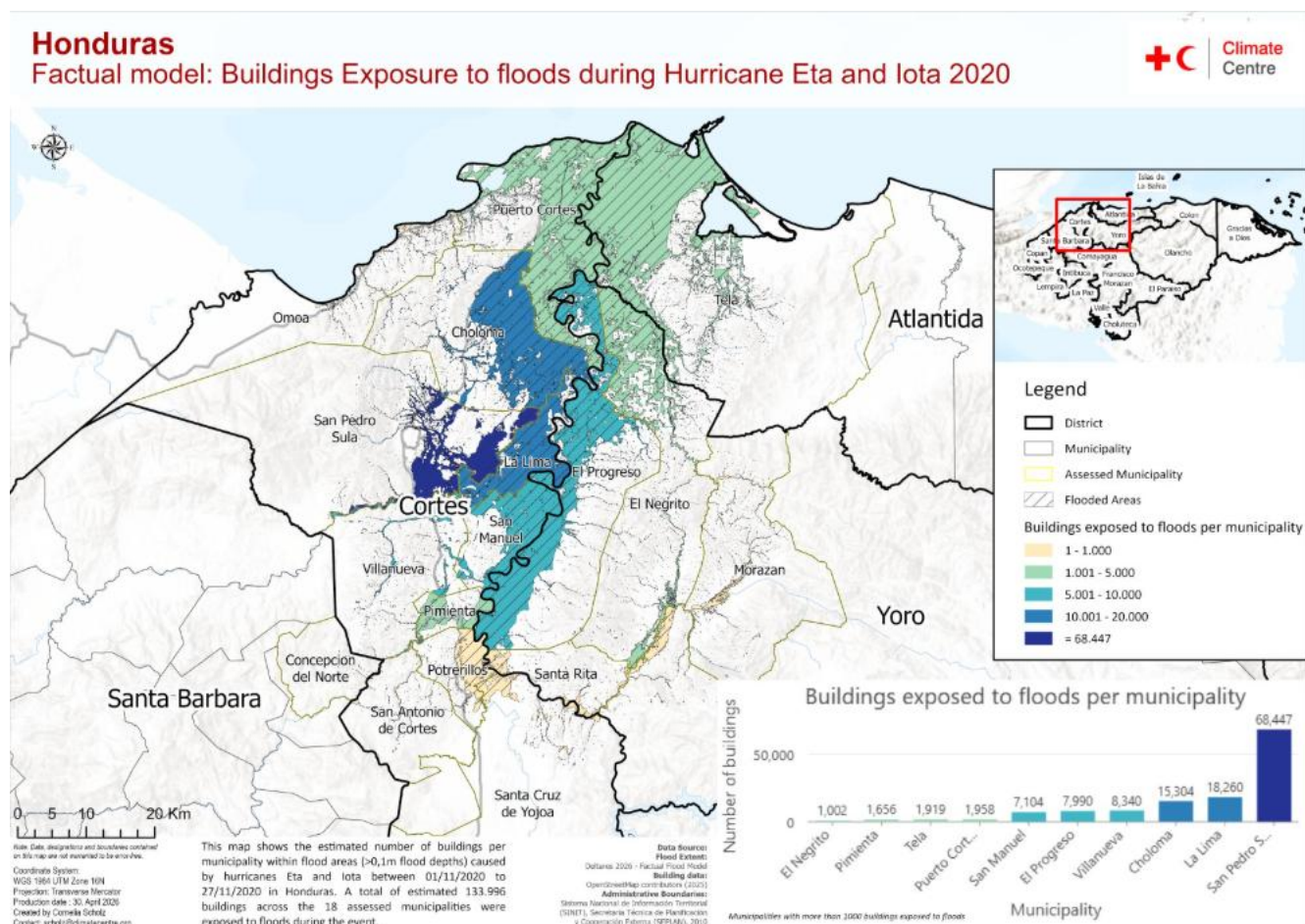


Figure 5644: Building exposure to flooding under factual scenario

The counterfactual exposure results are assessed in Figure (population) and Figure (buildings). Results indicate 613,059 total people exposed and 129,450 buildings. This results in a 2.9% increase in population exposure and a 3.5% increase in building exposure attributable to climate-change induced increases in rainfall intensities.

The results indicate that improved hydrological and flood modeling through the use of higher-resolution topography and land use in Phase II results in a clearer climate change induced increase in population and building exposure. These increases are expected due to the higher rainfall intensities in the factual scenario.

Land-use change (deforestation) counter-factual resulted in negligible impacts at an aggregate scale, but the limitations of the counter-factual noted above, as well as the possibility that deforestation may impact flood dynamics in particular locations, do not exclude deforestation as a potential driver of increased flood impacts in Honduras.

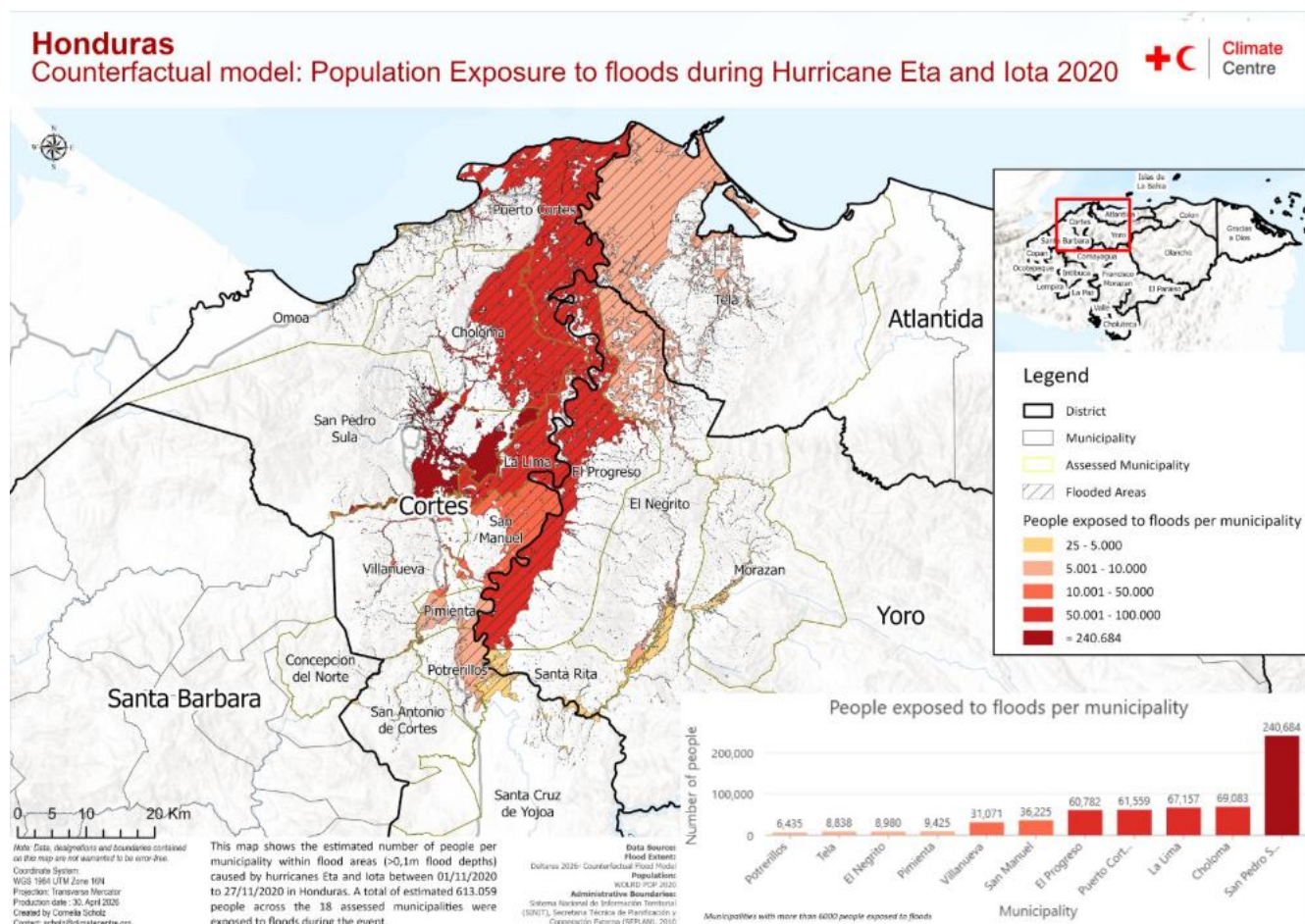


Figure 57: Population exposure to flooding under counter-factual rainfall scenario

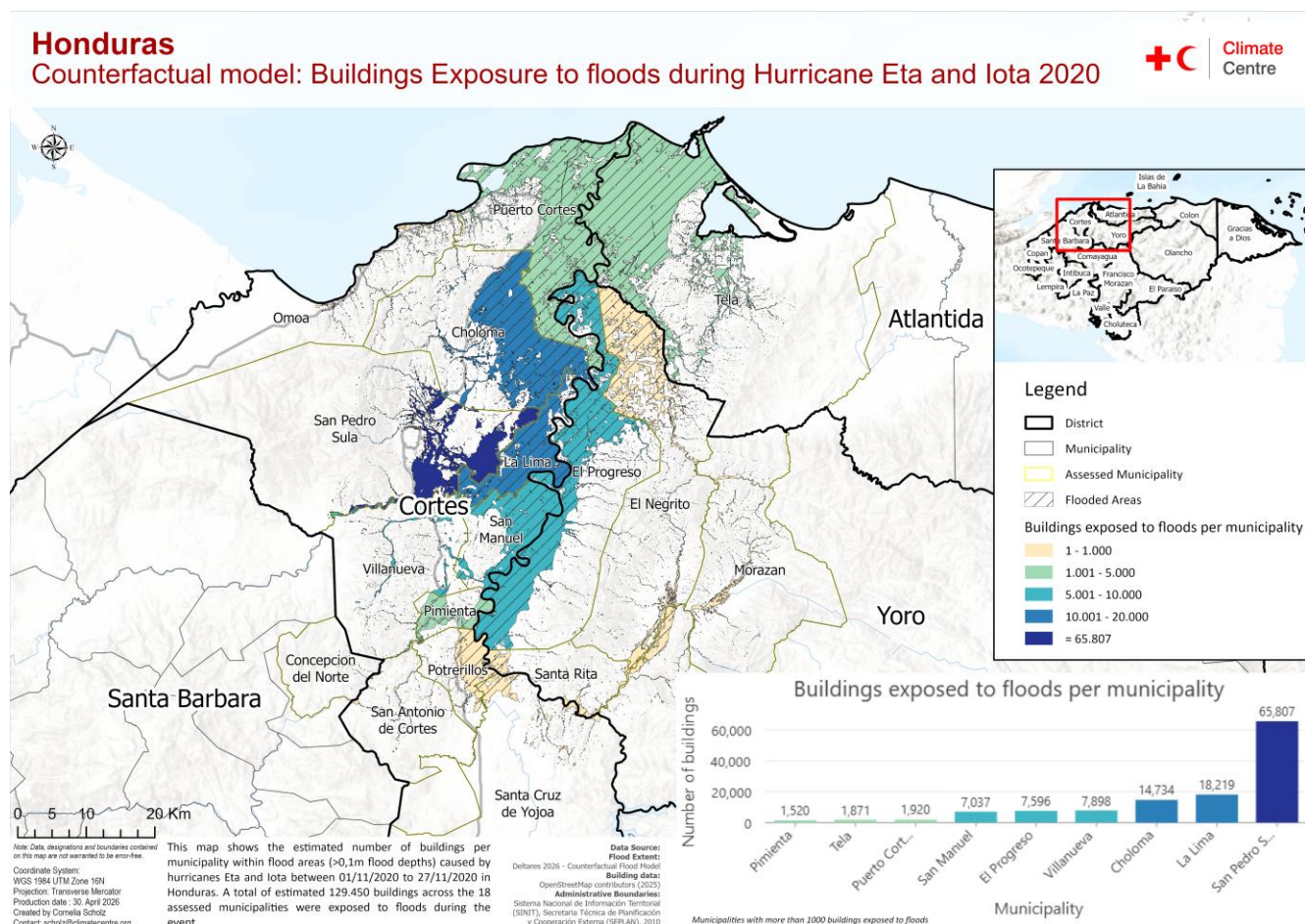


Figure 58: Building exposure to flooding under counter-factual rainfall scenario

6.4.3. Stakeholder and policy relevance

The updated hazard and attribution results for TC Eta and Iota are directly relevant to disaster risk management and adaptation planning in the Sula Valley, one of Honduras's most flood-prone and economically important regions. By separating the climate-driven and land-use-driven contributions to flood hazard, the analysis provides evidence that can inform two distinct areas of decision-making. First, the demonstrated potential amplification of flood hazard under a warmer climate strengthens the case for climate-informed early warning systems, forecast-based financing triggers, and infrastructure and drainage design standards that account for non-stationary flood risk, rather than historical climate alone. Second, the sensitivity of simulated flood depth to deforestation, and to the choice of land-cover dataset, underlines the importance of improved, higher-resolution land monitoring to support upstream catchment and land-use management in the Sula Valley, where continued conversion of forest to agricultural and urban land is likely to keep shaping local flood response. Taken together, these findings can support Honduran disaster risk management authorities and municipal planners, as well as humanitarian and development partners engaged in anticipatory action and flood risk reduction in the region, in prioritizing interventions that address both the climatic and non-climatic drivers of flood risk identified in this use case.

7. Use case 5: Durban Flooding (2022)

7.1. Summary of event

On 11–12 April 2022, exceptionally heavy rainfall caused catastrophic flooding and landslides along the eastern coast of South Africa, particularly in KwaZulu-Natal (KZN) and the eThekweni municipality, which includes the city of Durban. The event was described by South Africa's president as a national catastrophe and led to the declaration of a national state of disaster on 18 April 2022⁸¹. The event affected over 123,000 people, with 439 deaths, 80 people missing and over 30,000 people displaced⁸². The April floods were further compounded by a storm on May 21st 2022, causing further displacement and infrastructure damage in the eThekweni, Kink Cetshwaya and uMkhanyakude districts. The 2022 floods and landslides affected mostly informal settlements with high exposure and pre-existing (socio-economic) vulnerabilities, where households were still recovering from Tropical Storms Ana and Batsirai and the COVID-19 pandemic⁸³.

7.2. Observed hazards

Extreme, short-duration rainfall triggered widespread flooding and landslides across coastal eastern South Africa. In less than 24 hours, some locations received as much as 300 mm rainfall⁸⁴. The heavy rains triggered both fluvial and pluvial flooding, as well as land- and mudslides. The heavy rainfall event occurred after a particularly wet South African summer period, driven by La Niña conditions.

7.2.1. Type of hazards

- Extreme short-duration rainfall, with more than 350 mm of rain in two days recorded in parts of the affected area;
- Pluvial flooding, occurring as a direct consequence of extreme rainfall mostly in the (peri)urban areas;
- Fluvial flooding of 18 watercourses, including the Amanzimtoti, Umbilo, and Umgeni rivers;
- Landslides and mudslides, particularly in hilly coastal and urban areas.

7.2.2. Form of compounding

Heavy rainfall cascaded into pluvial and fluvial floods, as well as mud- and landslides. The pluvial and fluvial floods and the mud and landslides all compounded during the same time period in the same geographical area. Pre-existing wet conditions due to prior rainfall events, high socio-economic vulnerability and exposure all pre-conditioned and aggravated the intensity of the hazards and impacts. The area was still recovering economically from the 2021 riots and COVID-19 pandemic.

7.2.3. Driving dynamics

The April 2022 KwaZulu-Natal floods were primarily driven by a stationary cut-off low over the South African interior, combined with a blocking ridging anticyclone over the south-west Indian Ocean, which caused

⁸¹ Gazette, G., Gazette, R., & Notice, G. (2022). *Government notices • GoewermentskennisGewinGs CLASSIFICATION OF A PROVINCIAL DISASTER IN TERMS OF SECTION 23 OF THE DISASTER MANAGEMENT ACT (ACT NO. 57 OF 2002): IMPACT OF SEVERE WEATHER EVENTS*. www.gpwonline.co.za

⁸² Grab, S. W., & Nash, D. J. (2024). *A new flood chronology for KwaZulu-Natal (1836–2022): the April 2022 Durban floods in historical context*. *South African Geographical Journal*, 106(4), 476–497. <https://doi.org/10.1080/03736245.2023.2193758>; JOURNAL:JOURNAL:RSAG20;WGROU:STRING:PUBLICATION

⁸³ IFRC. (2022). *South Africa: Floods and landslides - Emergency Appeal No. MDRZA012 - South Africa*. <https://reliefweb.int/report/south-africa/south-africa-floods-and-landslides-emergency-appeal-no-mdrza012>

⁸⁴ Pinto, I., Zachariah, M., Wolski, P., Landman, S., Phakula, V., Maluleke, W., Bopape, M.-J., Engelbrecht, C., Jack, C., McClure, A., Bonnet, R., Vautard, R., Philip, S., Kew, S., Heinrich, D., Vahlberg, M., Singh, R., Arrighi, J., Thalheimer, L., ... Dipura, R. (2022). *Climate change exacerbated rainfall causing devastating flooding in Eastern South Africa*.

prolonged atmospheric instability and sustained heavy rainfall along the east coast rather than allowing the system to move rapidly offshore⁸⁵.

In addition to the exceptional rainfall intensity, impacts were also strongly driven by pre-existing vulnerabilities and exposure. The 2022 KwaZulu-Natal floods were driven by intersecting structural inequalities, rapid urbanisation, and systemic infrastructure failures. Apartheid-era spatial planning has concentrated marginalised populations in floodplains and other high-risk areas, while housing shortages and poverty have pushed people into informal settlements on riverbanks, wetlands, and steep slopes^{86,87,88}. These settlements are often built with highly vulnerable materials such as wood, mud, and corrugated metal, increasing exposure to damage and collapse⁸⁹. Urbanisation and governance challenges compounded this vulnerability. Rapid, largely unplanned expansion has outpaced infrastructure investment especially in highly exposed areas⁹⁰.

A critical driver was the failure of urban drainage systems. Durban's stormwater network is outdated and operates near capacity, having been designed for historical rainfall patterns and smaller catchments. During the 2022 event, undersized pipes, blocked channels, and poor maintenance triggered cascading failures, including overtopping and widespread flooding beyond mapped floodplains⁹¹. Debris, sediment, invasive vegetation, and plastic waste further clogged waterways, restricting flow and intensifying inundation.

Preparedness systems also showed significant weaknesses. Although early warnings were issued, communication gaps meant that they reached only a limited portion of the population, with many recipients

⁸⁵ Thoithi, W., Blamey, R. C., & Reason, C. J. C. (2023). *April 2022 floods over East Coast South Africa: Interactions between a mesoscale convective system and a coastal meso-low*. *Atmosphere*, 14(1), 78. <https://doi.org/10.3390/atmos14010078>

⁸⁶ Bouchard, J.-P., Pretorius, T. B., & Kramers-Olen, A. L. (2023). *Global warming and psychotraumatology of natural disasters: the case of the deadly rains and floods of April 2022 in South Africa*. <http://hdl.handle.net/10566/9150>

⁸⁷ Byaruhanga, N., Kibirige, D., & Mkhonta, G. (2025). *Understanding South Africa's Flood Vulnerabilities and Resilience Pathways: A Comprehensive Overview*. *Water* 2025, Vol. 17, Page 2608, 17(17), 2608. <https://doi.org/10.3390/W17172608>

⁸⁸ Dlamini, S., Nhleko, B., & Ubisi, N. (2025). *Understanding Socioeconomic Risk and Vulnerability to Climate Change-Induced Disasters: The Case of Informal Settlements in KwaZulu-Natal, South Africa*. *Journal of Asian and African Studies*, 60(7), 4594–4613. <https://doi.org/10.1177/00219096241275398>

⁸⁹ IFRC. (2025). *South Africa Floods and landslides Final Report Emergency appeal №: MDRZA012*. <https://www.gov.za/news/speeches/president-cyril-ramaphosa-declaration-national-state-disaster-respond-widespread>

⁹⁰ Byaruhanga, N., Kibirige, D., & Mkhonta, G. (2025). *Understanding South Africa's Flood Vulnerabilities and Resilience Pathways: A Comprehensive Overview*. *Water* 2025, Vol. 17, Page 2608, 17(17), 2608. <https://doi.org/10.3390/W17172608>

⁹¹ Moosa, B., Gumbo, T., Mphambukeli, T., & Simelane, T. (2026). *Urban Drainage Failure in Durban's 2022 Floods and a SUDS Pathway to Improved Resilience*. REAL CORP 2026 Proceedings/Tagungsband. <https://doi.org/10.48494/REALCORP2026.9054>

lacking clarity on how to respond^{92,93}. Overall, deeply rooted inequalities, inadequate infrastructure, and limited preparedness combined to produce high levels of flood risk.

7.2.4. Intensity/Extremity/Magnitude

Rainfall totals vary strongly across observation stations, with some stations registering over 350mm in 2 days. Based on reanalysis of past observations, this rainfall intensity has a 1-in-20 years return period under the current climate⁹³. Total flooded area: 373,868 ha in Eastern Cape, and 137,601 ha in Kwazulu-Natal, with 51,601 ha cropland inundated⁹⁴.

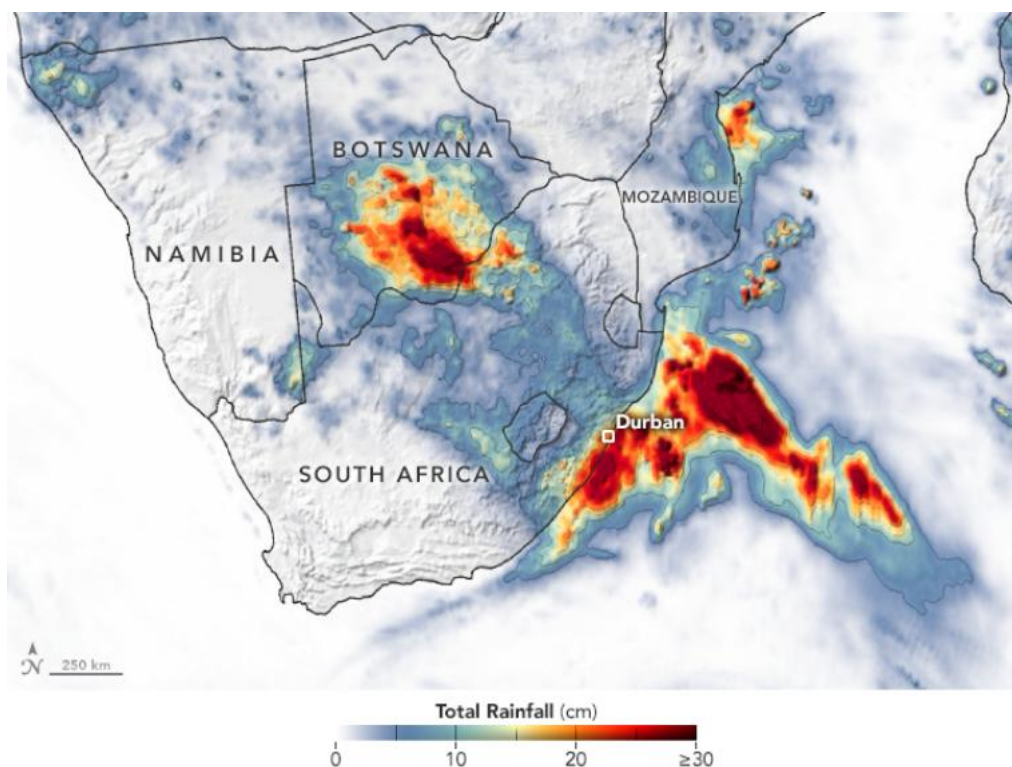


Figure 59: Satellite-based estimate of rainfall over a seven-day period ending on April 13, 2022. The darkest reds reflect the highest rainfall amounts, based on GPM estimates⁹⁵.

⁹² Byaruhanga, N., Kibirige, D., & Mkhonta, G. (2025). *Understanding South Africa's Flood Vulnerabilities and Resilience Pathways: A Comprehensive Overview*. *Water* 2025, Vol. 17, Page 2608, 17(17), 2608. <https://doi.org/10.3390/W17172608>

⁹³ Pinto, I., Zachariah, M., Wolski, P., Landman, S., Phakula, V., Maluleke, W., Bopape, M.-J., Engelbrecht, C., Jack, C., McClure, A., Bonnet, R., Vautard, R., Philip, S., Kew, S., Heinrich, D., Vahlberg, M., Singh, R., Arrighi, J., Thalheimer, L., ... Dipura, R. (2022). *Climate change exacerbated rainfall causing devastating flooding in Eastern South Africa*. World Weather Attribution Study. <https://www.worldweatherattribution.org/wp-content/uploads/WWA-KZN-floods-scientific-report.pdf>

⁹⁴ FAO. (2022). *A rapid geospatial analysis of the flood impacts on crops in KwaZulu-Natal and Eastern Cape provinces of South Africa in 2022*. FAO. <https://doi.org/10.4060/cc1046en>

⁹⁵ NASA. (2022). *Deluge in South Africa*. <https://science.nasa.gov/earth/earth-observatory/deluge-in-south-africa-149720/>

7.3. Observed impacts

7.3.1. Quantitative impacts

There are slight variations in reported impacts. Based on IFRC and Government data, approximately 27,069 households were directly affected – translating to over 135,000 people. 456 lost their lives, and 88 people remained missing as of April 2025⁹⁶. Economic damages exceeded ZAR 17 billion (~2 Billion USD)⁹⁷.

Table 7: Flood impacts by sector derived from IFRC, Presidential Climate Commission, and Grab and Nash (2023)

Impact	Number	Source
Fatalities	456	IFRC, 2025 ⁹⁸
People missing	88	IFRC, 2025
Houses affected	22,120	IFRC, 2025
Schools damaged	600	PCC, 2023 ⁹⁹
Health facilities damages	84	PCC, 2023
Critical infrastructure	R10 billion	PCC, 2023
Overall damages	R17 billion	PCC, 2023
Damages to the manufacturing sector	R431 million	PCC, 2023
Warehousing and logistics sector	R33 million	PCC, 2023
Construction sector	R18 million	PCC, 2023
People temporary unemployed	45,000	Grab and Nash, 2023 ¹⁰⁰

7.3.2. Qualitative impacts and responses

Qualitative impacts

The April–May 2022 KwaZulu-Natal floods caused severe and cascading impacts across communities and infrastructure systems. The disaster led to loss of life, widespread displacement, and the destruction of homes

⁹⁶ IFRC. (2025). *South Africa Floods and landslides Final Report Emergency appeal No: MDRZA012*.

<https://www.ifrc.org/appeal/south-africa-floods-and-landslides-mdrza012-4>

⁹⁷ Grab, S. W., & Nash, D. J. (2024). A new flood chronology for KwaZulu-Natal (1836–2022): the April 2022 Durban floods in historical context. *South African Geographical Journal*, 106(4), 476–497. <https://doi.org/10.1080/03736245.2023.2193758>

⁹⁸ IFRC. (2025). *South Africa Floods and landslides Final Report Emergency appeal No: MDRZA012*. <https://www.ifrc.org/appeal/south-africa-floods-and-landslides-mdrza012-4>

⁹⁹ Presidential Climate Commission. (2023). *A critical analysis of the impacts of and responses to the April–May 2022 floods in KwaZulu-Natal*. Republic of South Africa: Rosebank, South Africa.

¹⁰⁰ Grab, S. W., & Nash, D. J. (2024). A new flood chronology for KwaZulu-Natal (1836–2022): The April 2022 Durban floods in historical context. *South African Geographical Journal*, 106(4), 476–497.

and livelihoods, particularly in informal settlements located in high-risk areas¹⁰¹. Critical infrastructure, including water, transport, and health services, was heavily damaged, resulting in prolonged service disruptions and reduced access to essential resources. These impacts disrupted economic activity and food access, while also increasing public health risks and psychological distress among affected populations.

Responses

Early warnings were issued by the South African Weather Service and eThekweni Municipality prior to the floods, but their reach and effectiveness were limited, with many recipients unsure how to act in response to them¹⁰² and given the timing of the floods during the night¹⁰³. Overall, early warning and preparedness systems showed significant gaps, reflecting weak communication and limited capacity to translate forecasts into actionable guidance. However, outcomes varied: while formal warning systems had little impact, a community-based early warning approach using local communication networks successfully enabled timely action and prevented fatalities in at least one informal settlement¹⁰⁴.

Response efforts were largely reactive, with authorities prioritising emergency response and recovery over pre-event risk reduction despite prior flood experience^{84,105}. Following the disaster, government and partners mobilised shelters, humanitarian relief, and large-scale rescue operations, which helped stabilise affected communities but were constrained by coordination challenges and delays.

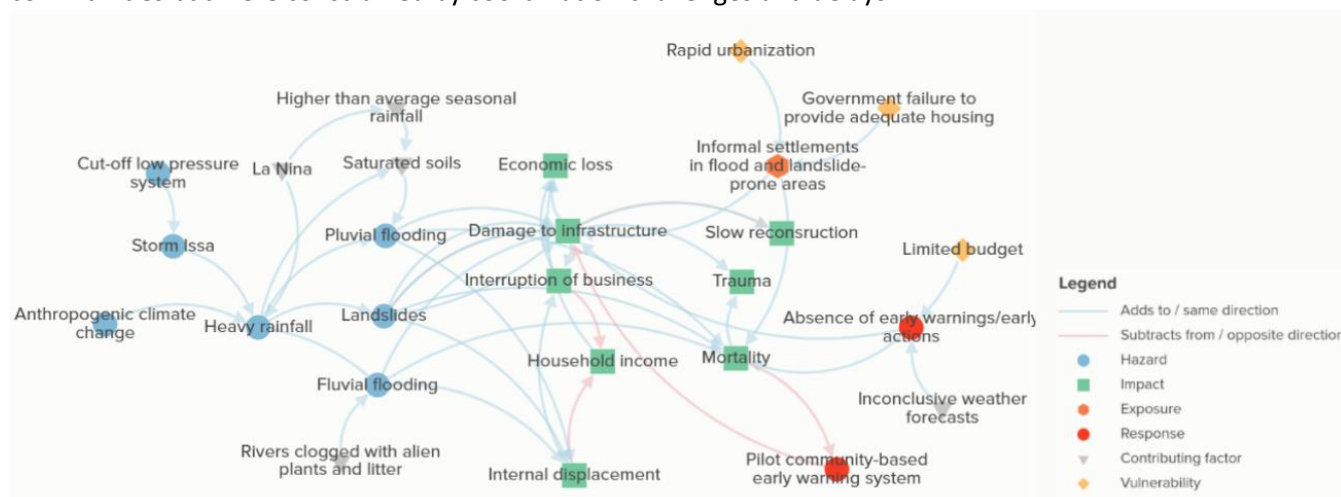


Figure 60: Qualitative causal mapping of complex climate risk derived from event document analysis

¹⁰¹ Presidential Climate Commission. (2023). *A critical analysis of the impacts of and responses to the April–May 2022 floods in KwaZulu-Natal*. Republic of South Africa: Rosebank, South Africa.

¹⁰⁶ Pinto, I., Zachariah, M., Wolski, P., Landman, S., Phakula, V., Maluleke, W., Bopape, M.-J., Engelbrecht, C., Jack, C., McClure, A., Bonnet, R., Vautard, R., Philip, S., Kew, S., Heinrich, D., Vahlberg, M., Singh, R., Arrighi, J., Thalheimer, L., ... Dipura, R. (2022). *Climate change exacerbated rainfall causing devastating flooding in Eastern South Africa*.

¹⁰⁷ IFRC. (2025). *South Africa Floods and landslides Final Report Emergency appeal No: MDRZA012*. <https://www.gov.za/news/speeches/president-cyril-ramaphosa-declaration-national-state-disaster-respond-widespread>

¹⁰⁴ Sutherland, C., Martel, P., & Hannan, S. (2023, March 8). *Empowering vulnerable communities against the impacts of climate change: An innovative community-based flood early warning system in eThekweni Municipality*.

¹⁰⁵ Madzivhandila, T. S., & Maserumule, M. H. (2022). *The irony of a “fire fighting” approach towards natural hazards in South Africa: Lessons from flooding disaster in KwaZulu-Natal*. *Journal of Public Administration*, 57(2), 191–194. https://doi.org/10.10520/ejc-jpad_v57_n2_a1

7.4. Modeling framework

7.4.1. Hazard modeling

Flood hazards are simulated using the Super-Fast INundation of CoastS (SFINCS) model¹⁰⁶. SFINCS is a reduced-physics solver used to simulate compound (pluvial, fluvial, and coastal) flooding in coastal areas. It solves simplified equations of mass and momentum to simulate overland flow in two dimensions, accurately estimating flooding while being computationally efficient. For the Durban case, we use elevation data from FABDEM at 30m resolution¹⁰⁷ and from GEBCO at 450m¹⁰⁸ to fill out missing data. Roughness data are retrieved from Copernicus Global Land Service¹⁰⁹ and infiltration data from the GCN250 dataset¹¹⁰. The precipitation forcing data is obtained from ERA5 at 0.25 degrees and hourly resolution¹¹¹.

7.4.2. Impact modeling

Impact modelling is done with the Delft-FIAT model, which quantifies building damages and the population exposed to floods. Delft-FIAT combines flood extent and depths with exposure and vulnerability data, enabling impact modeling at the individual building level.

Exposure mapping

For building exposure, including location and footprint, we use data from OpenStreetMap. And for population data, we retrieve from the WorldPop 2020 UN adjusted database at 100m resolution.

Vulnerability modelling

Vulnerability curves used to estimate the economic damages from flooding for different types of building are obtained from Huizinga et al., 2017¹¹².

7.5. Attribution modeling framework

7.5.1. Event definition

The simulation here spans from 2022-04-10 to 2022-04-13 at an hourly rate. The area of analysis consists of 2064,51 km² along the coast of Durban. The simulation is done at 100m resolution. Figure shows the area of the event analysed, and the main forcing, precipitation, over the timeline considered.

¹⁰⁶ Leijnse, T. W. B., van Ormondt, M., Nederhoff, K., & van Dongeren, A. (2021). *Modeling compound flooding in coastal systems using a computationally efficient reduced-physics solver: Including fluvial, pluvial, tidal, wind- and wave-driven processes*. Coastal Engineering, 163, 103796. <https://doi.org/10.1016/j.coastaleng.2020.103796>

¹⁰⁷ Hawker, L., Uhe, P., Paulo, L., Sosa, J., Savage, J., Sampson, C., & Neal, J. (2022). *A 30 m global map of elevation with forests and buildings removed*. Environmental Research Letters, 17(2), Article 024016. <https://doi.org/10.1088/1748-9326/ac4d4f>

¹⁰⁸ <https://www.gebco.net/news/gebco-2014-grid>

¹⁰⁹ Buchhorn, M., Smets, B., Bertels, L., Lesiv, M., Tsendbazar, N.-E., Herold, M., Fritz, S., & Lesiv, M. (2021). *Global land characterisation using land cover fractions at 100 m resolution*. Remote Sensing of Environment, 259, Article 112409. <https://doi.org/10.1016/j.rse.2021.112409>

¹¹⁰ Jaafar, H. H., Ahmad, F. A., & El Beyrouthy, N. (2019). *GCN250, New Global Gridded Curve Numbers for Hydrologic Modeling and Design*. Scientific Data, 6, Article No. 145. <https://doi.org/10.1038/s41597-019-0155-x>

¹¹¹ Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., Nicolas, J., Peubey, C., Radu, R., Schepers, D., Simmons, A., Soci, C., Abdalla, S., Abellan, X., Balsamo, G., Bechtold, P., Biavati, G., Bidlot, J.-R., Bonavita, M., ... Thépaut, J.-N. (2020). *The ERA5 global reanalysis*. Quarterly Journal of the Royal Meteorological Society, 146(730), 1999–2049. <https://doi.org/10.1002/qj.3803>

¹¹² Huizinga, J., DE, M., & Szewczyk, W. (2017). *Global flood depth-damage functions: Methodology and the database with guidelines*.

Durban_April2022 overview (Durban2022)

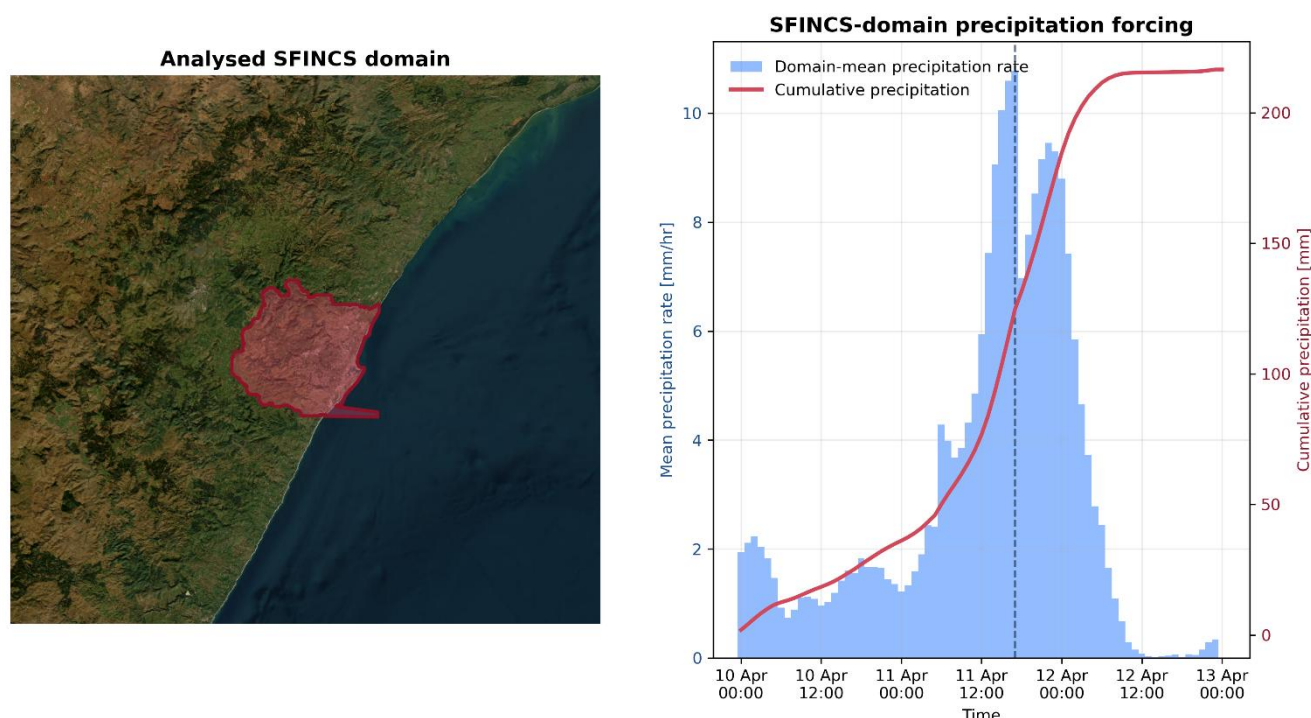


Figure 61: Left: Satellite basemap of the Durban study area, with the SFINCS model domain highlighted in red. Right: Time series of precipitation forcing over the domain from the ERA5 hourly forcing. Blue bars show the domain-mean precipitation rate in mm/hr, while the red curve shows cumulative precipitation in mm.

7.5.2. Factual and counterfactual simulations

While the factual event consists of historical precipitation forcing (see Figure), we consider two methods for generating counterfactuals at pre-industrial (PI) warming levels, in order to compare the sensitivity of attribution statements regarding their methods.

The first method consists of applying a delta factor on the precipitation values of the factual event based on the Clausius–Clapeyron (CC) relation, which implies that every degree of warming leads to a 7% change in saturation vapor pressure and, consequently, precipitation¹¹³. In this report, we consider the counterfactual as the PI version of the factual Durban event, which means we reduce the precipitation values from ERA5 by 8% as a result of the warming level difference between 2022 and PI levels (1880-1900).

The second method is based on the Destination Earth ClimateDT storylines dataset (CDT). These consist of fully coupled global simulations from the IFS-FESOM model, where the atmospheric model is spectrally nudged toward the large-scale circulation patterns from ERA5. This ensures that the simulations are dynamically constrained reconstructions of the large-scale patterns of historical events, with thermodynamical differences being largely attributed to global warming changes from the models. There are 3 versions: past (PI), present and future scenarios. For attribution, we consider the past and present scenarios. Small-scale spatial differences between the two runs cannot be attributed to climate change forcing. To isolate the climate signal, we use also

¹¹³ Goulart, H. M. D., Athanasiou, P., van Ginkel, K., van der Wiel, K., Winter, G., Pinto, I., & van den Hurk, B. (2025). *Exploring coastal climate adaptation through storylines: Insights from cyclone Idai in Beira, Mozambique*. Cell Reports Sustainability, 2(1), 100270. <https://doi.org/10.1016/j.crsus.2024.100270>

the delta approach but defined as the difference in total precipitation over the area analysed between the two scenarios.

7.6. Results

7.6.1. Factual hazards and impacts

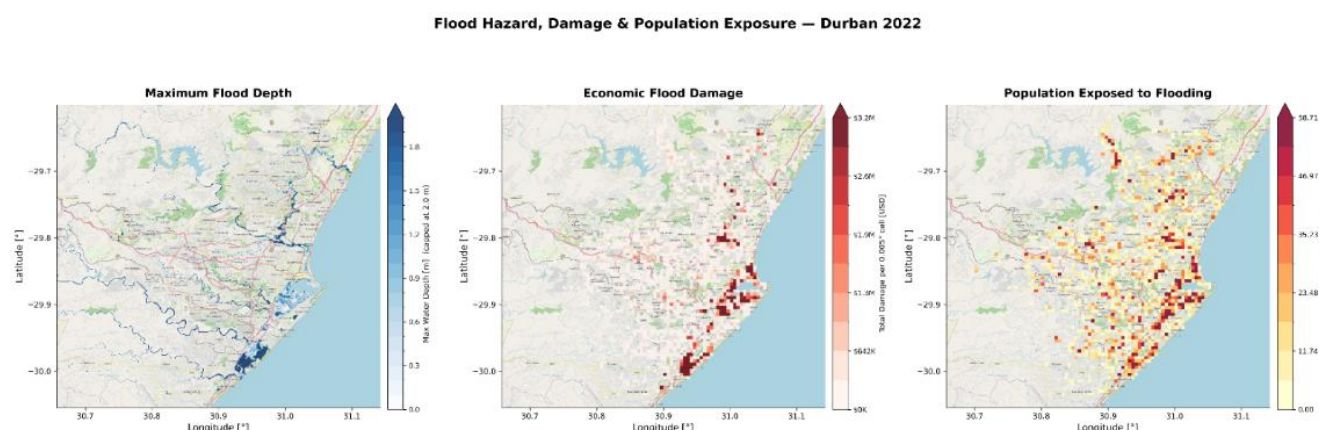


Figure 62: Spatial distribution of the 2022 Durban flood factual scenario. Left panel: Maximum simulated flood depth (m). Centre panel: Total economic damage (USD) per grid cell. Right panel: Exposed population count per grid cell.

In our simulations for the factual event, most of the precipitation in the region drains to the waterways in the valleys as a consequence of the hilly topography (Figure). The water moves towards the coast and converges towards the Harbour and Southwest areas of Durban, where most of the flooding happens, with large areas showing inundations above 1m in depth. Additionally, the areas along the two larger rivers north of the city indicate high water levels. In quantitative terms, the simulations show a total flood extent of 101.6 km² and an accumulated flood volume of 146.86 Mm³. Across the inundated areas, the mean water depth is 1.45 meters.

The zones of concentrated flooding align with the spatial distribution of economic damage and population exposure. Delft-FIAT modeling results (Figure) show that economic damage is predominantly concentrated in the Harbour and Southwest sectors, which function as the primary impact hotspots. Secondary clusters of structural damage align with the floodplains of the two river systems north of Durban. Population exposure follows a similar trend, alongside a more widespread distribution. In total, the factual event results in \$852,4 million in total economic damage, affecting 23,653 buildings and exposing 20,624 people, with a mean damage of \$36,036 per building.

GIS based exposure mapping based on WorldPop 2020 data and OSM building footprints produces quite different results (Figure and Figure below). GIS population exposure mapping results in 142,156 people exposed and 27,386 buildings. The discrepancy between Delft-FIAT modeling results and the GIS analysis is large and would require further exploration but also highlights the potentially large differences in results that can occur when using different datasets and methods.

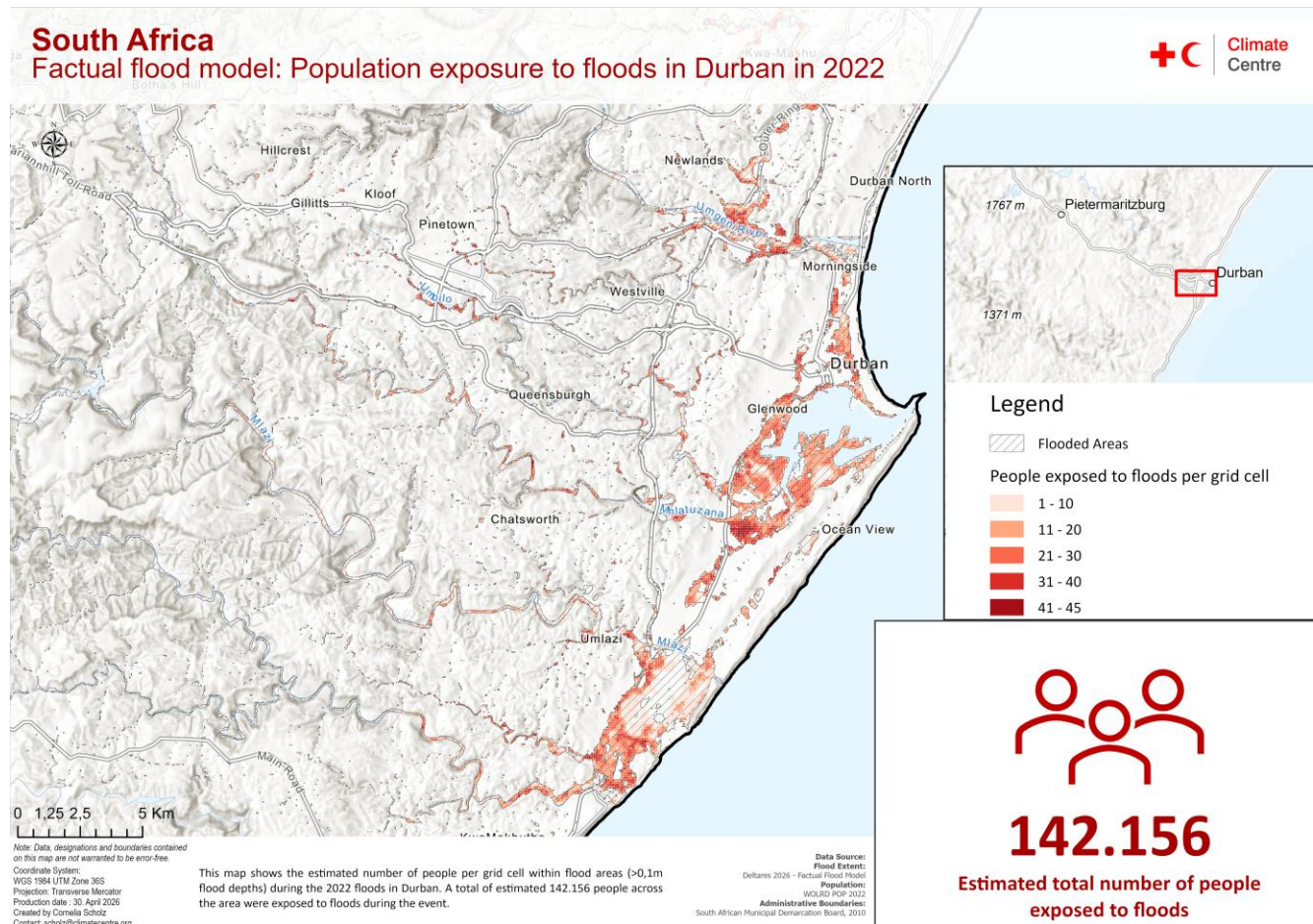


Figure 63: GIS population exposure mapping based on WORLD POP 2022 gridded population dataset and modeled flood extent

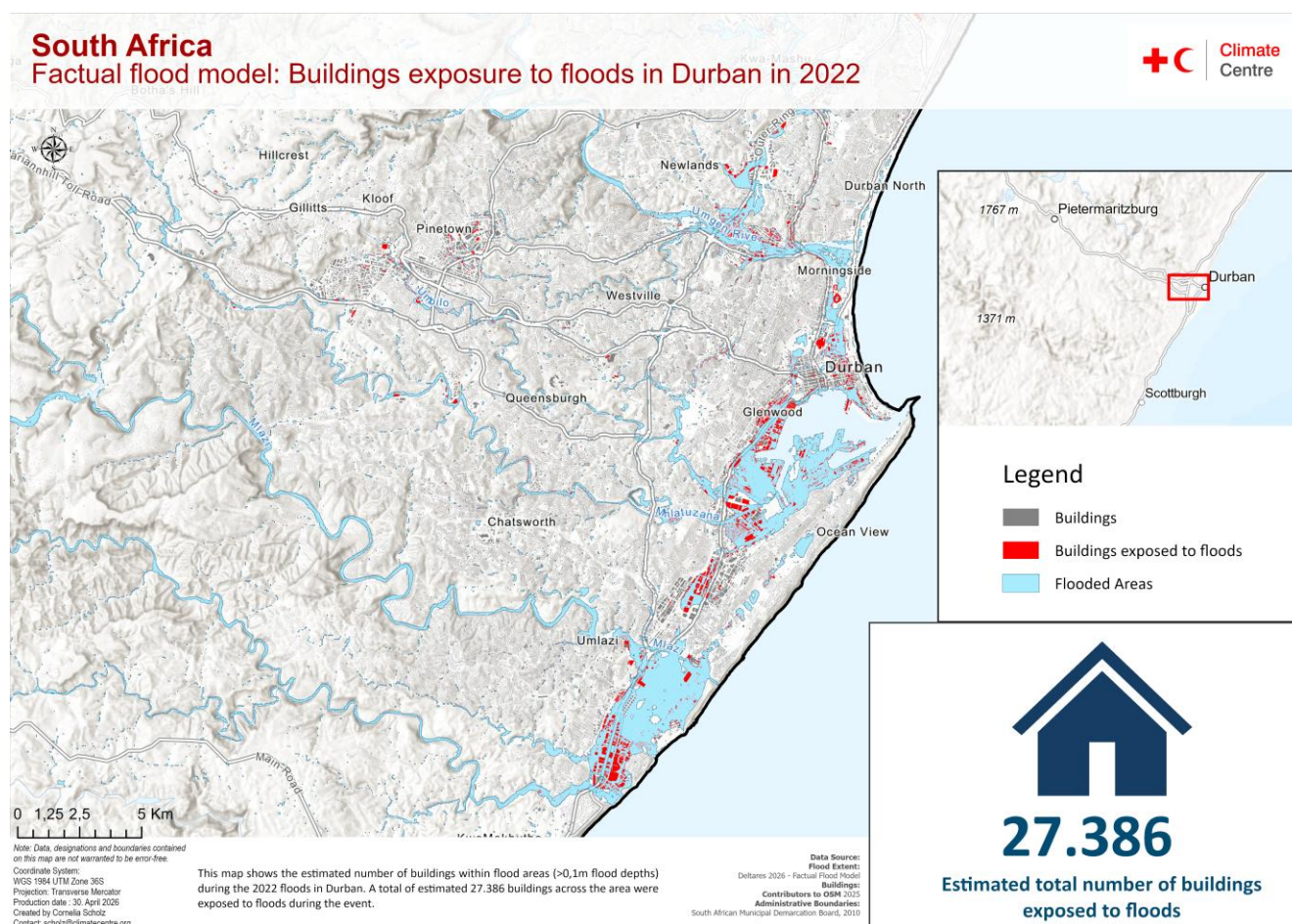
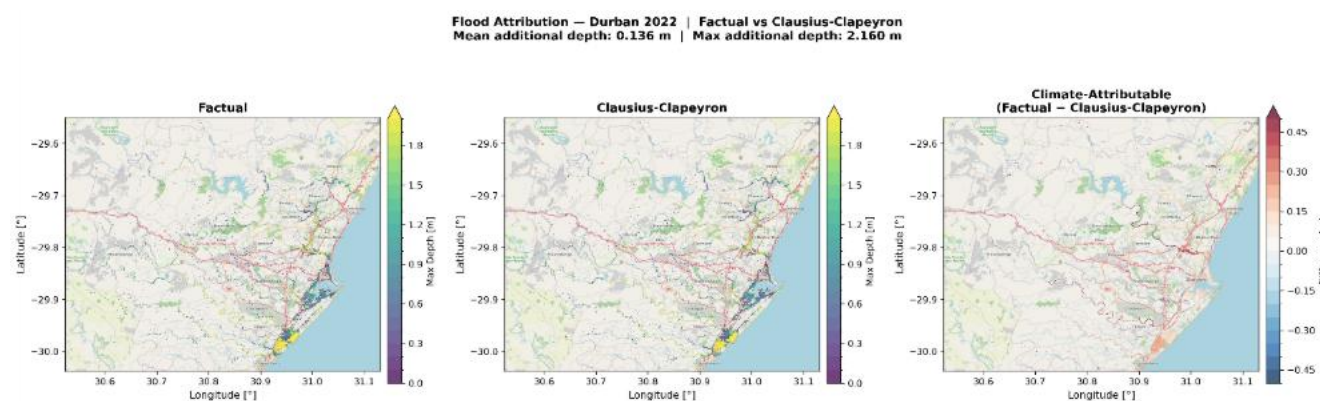


Figure 64: GIS building exposure mapping based on OSM building footprints and modeled flood extent

7.6.2. Attribution results

The CC counterfactual method shows an overall decrease in flood area under pre-industrial climate conditions as a result of less precipitation (Figure). The flood hotspots, such as the Harbor and Southwest areas, show a decrease in flood depths, just like all rivers in the region. In general, the method attributes a 9.45% increase in flood volume (+13.88 Mm³), a 3.86% increase in flood extent (+3.91 km²), and a 5.82% increase in mean depth (+0.09 m) to climate change. The CDT method suggests larger differences. It attributes an 11.82% increase in flood volume (+17.36 Mm³), a 4.85% increase in extent (+4.92 km²), and a 7.32% increase in depth (+0.11 m) to climate change.



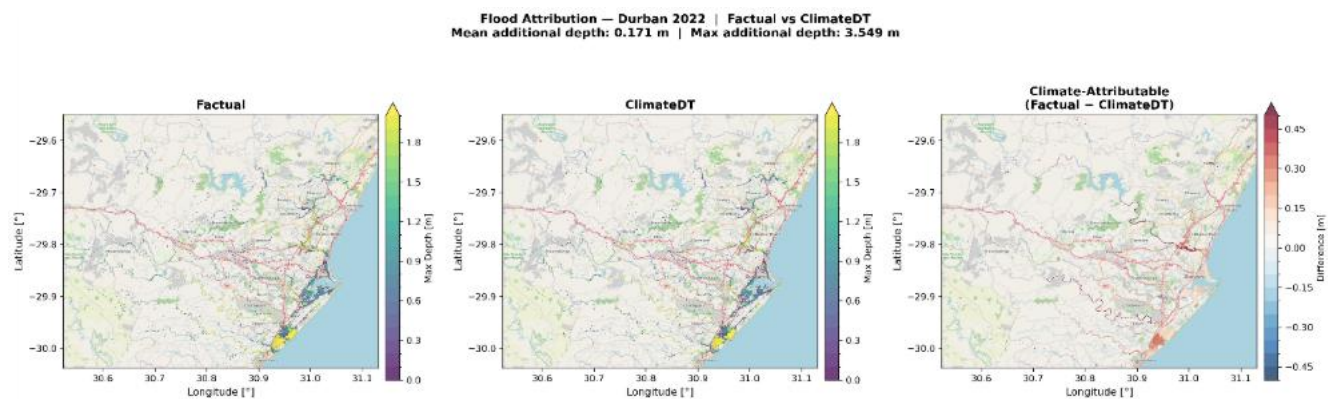


Figure 65: Flood hazard for the Durban 2022 event, comparing (left) the factual scenario against two counterfactual attribution methods: (middle, top row) a Clausius-Clapeyron (C-C) thermodynamic scaling counterfactual, and (middle, bottom row) a ClimateDT-based counterfactual. The right column shows the climate-attributable difference (factual minus counterfactual) for each method. Sequential color scales indicate absolute flood depth (m); the diverging scale highlights areas of increased or reduced depth attributable to the precipitation perturbation.

Using the Delft-FIAT model and under the CC method, 9.3% (\$79.3 million) of the total economic damage is attributed to climate change (Figure). The CC climate signal also accounts for 4.9% (1,152) of the affected buildings, and 4.7% (\$1,679) of the mean damage per building. The CDT method attributes 11.6% (\$99.0 million) of the total economic damage to the climate change signal. It also shows a decrease of 6.0% (1,427) in the total affected buildings, and 5.9% (\$2,142) of the mean damage per building. Additionally, the plots show the climate change effects to be strongest in the high damage areas in the south.

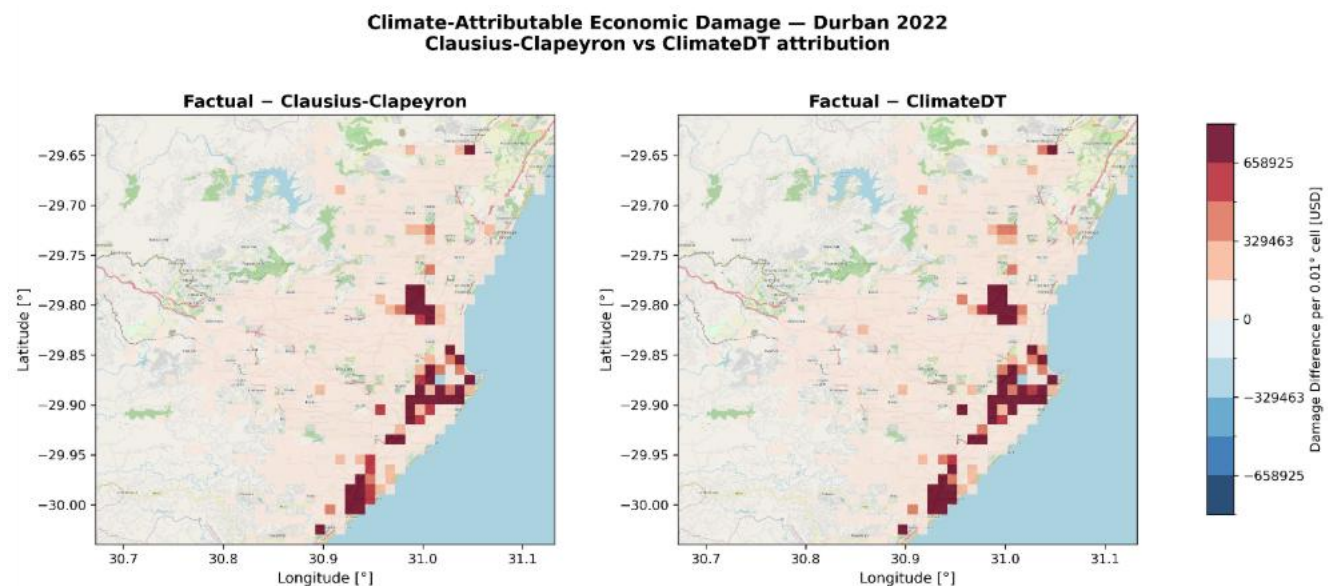


Figure 66: Difference in gridded economic damage from Durban floods for (left) Clausius-Clapeyron and (right) ClimateDT. Diverging scale highlights areas of increased or reduced damage attributable to the precipitation perturbation.

The population exposure attribution to climate change behaves similarly to the economic damage (Figure). The CC method reveals that climate change increased the exposed population by 3.3% (686 people). The CDT method is not much different, suggesting an increase of 4.1% (846 people) in the exposed population. In contrast to the

economic damage, however, the changes in population exposure are more spatially distributed and less concentrated in hotspot areas.

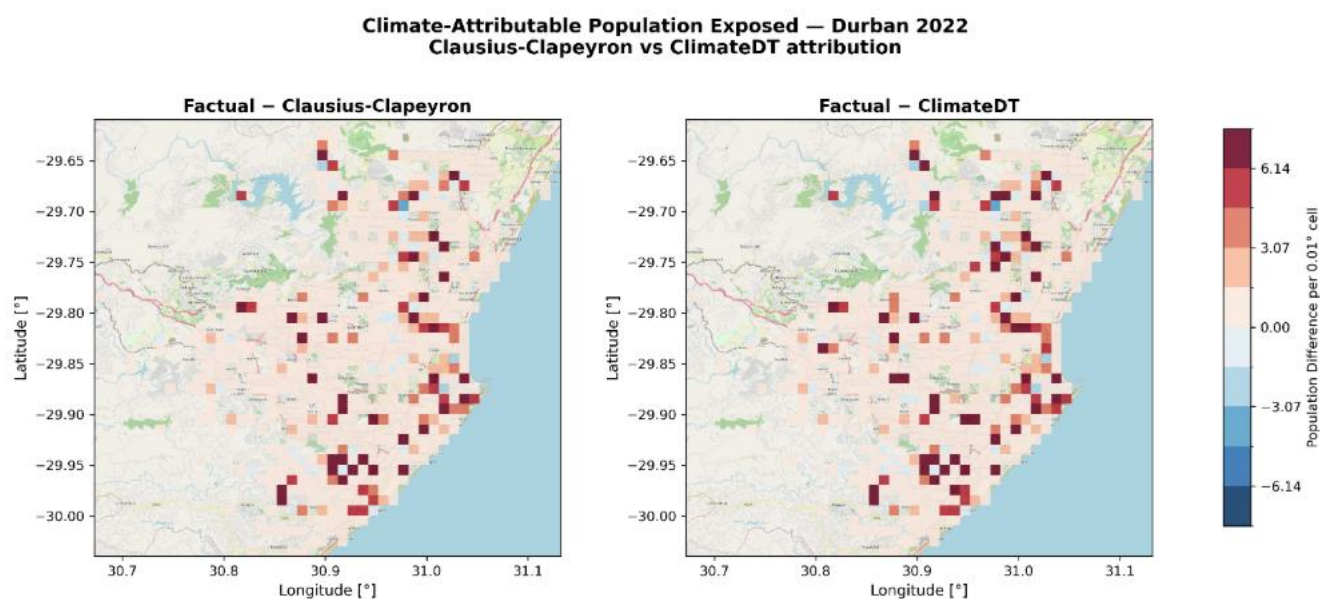


Figure 67: Same as Figure , but for exposed population in both scenarios.

When comparing the two approaches across the main aggregated metrics (Figure), we find the two approaches to not greatly diverge from one another. While the climate change attribution from the ClimateDT method is higher than the CC method, they both estimate climate change as an amplifier of hazards and impacts for the Durban case, and at similar orders of magnitude. The CC method translates the signal via thermodynamic scaling of precipitation intensity, while ClimateDT method uses a signal based directly on precipitation simulations. That both methods yield results within the same order of magnitude (9-12% for damage) suggests the climate change signal might not depend too much on the climate attribution method considered. Nevertheless, given that we only explored two alternative methods, we recommend considering extra methods for the generation of counterfactuals. This would offer a more robust exploration of the role of counterfactual methods in the resulting impact attribution statements.

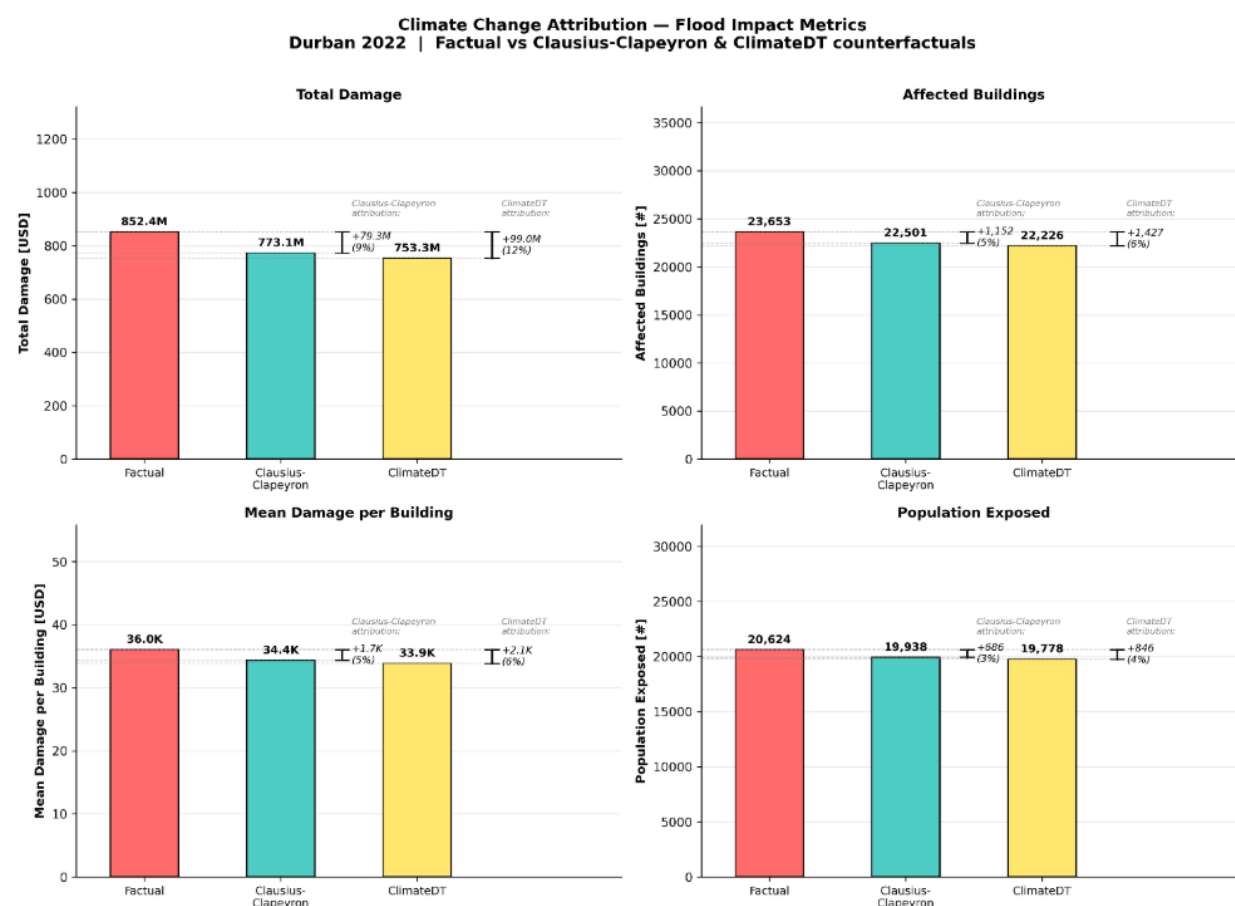


Figure 68: Comparison between factual and counterfactual scenarios. Bars show total damage (USD), number of affected buildings, mean damage per affected building, and population exposed. Annotated differences represent the estimated climate-attributable contribution among the two different methods: Clausius-Clapeyron and ClimateDT, expressed in absolute and relative terms.

GIS Mapping results

The GIS-based exposure mapping (Figure) shows very similar results with 133,822 people exposed under the ClimateDT counterfactual and 135,433 under the CC counterfactual. This results in a 6.2% difference for the ClimateDT and a 4.9% difference for the CC counterfactual. Similarly, building exposure mapping results (Figure) show a 6.6% difference for ClimateDT counterfactual and 5.2% difference for the CC counterfactual. These results are in line with those from Delft-FIAT modeling even if the factual population and building exposure results are very different using the GIS mapping approach.

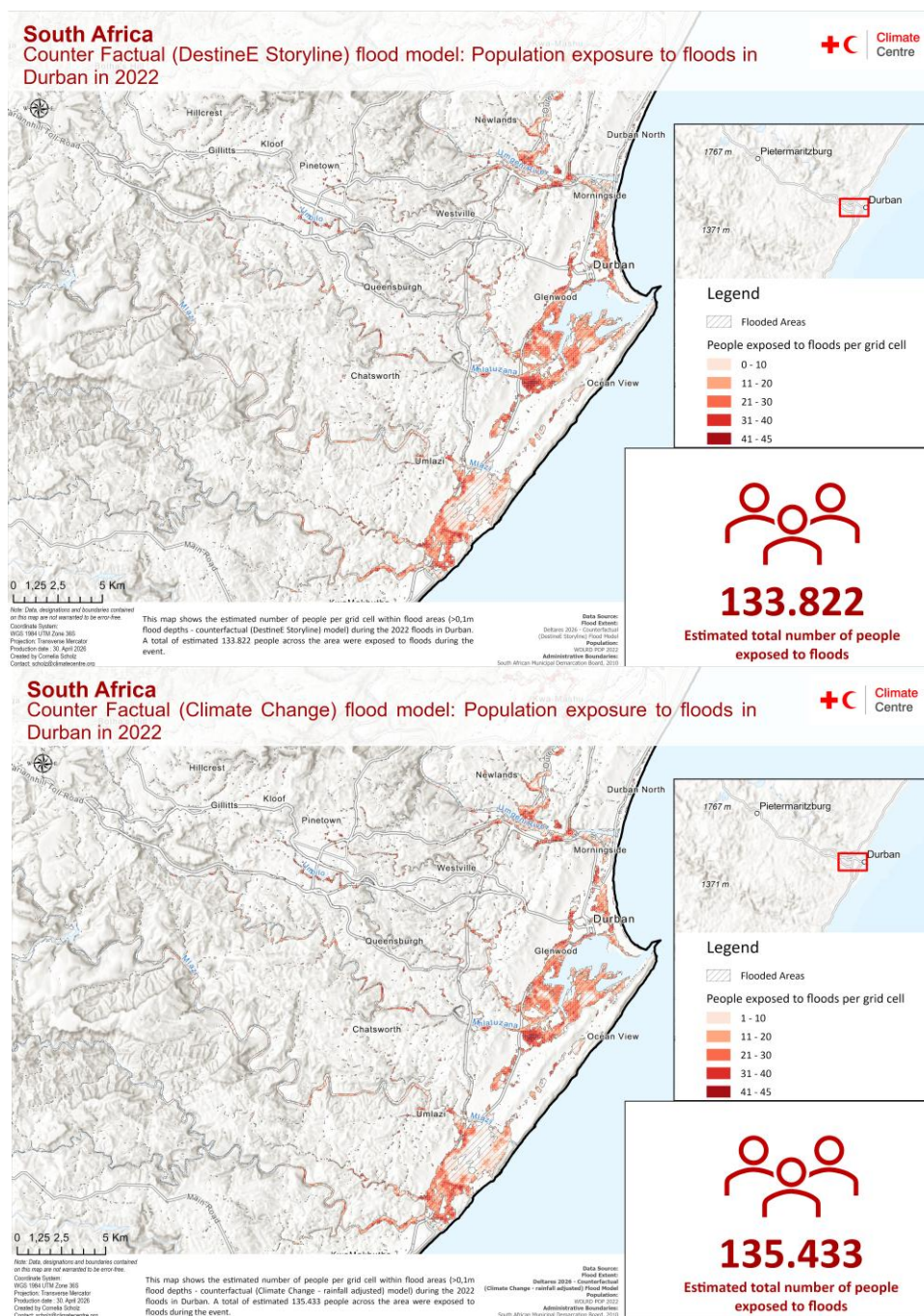


Figure 69: GIS based population exposure mapping for DestineE (upper panel) and CC (lower panel)

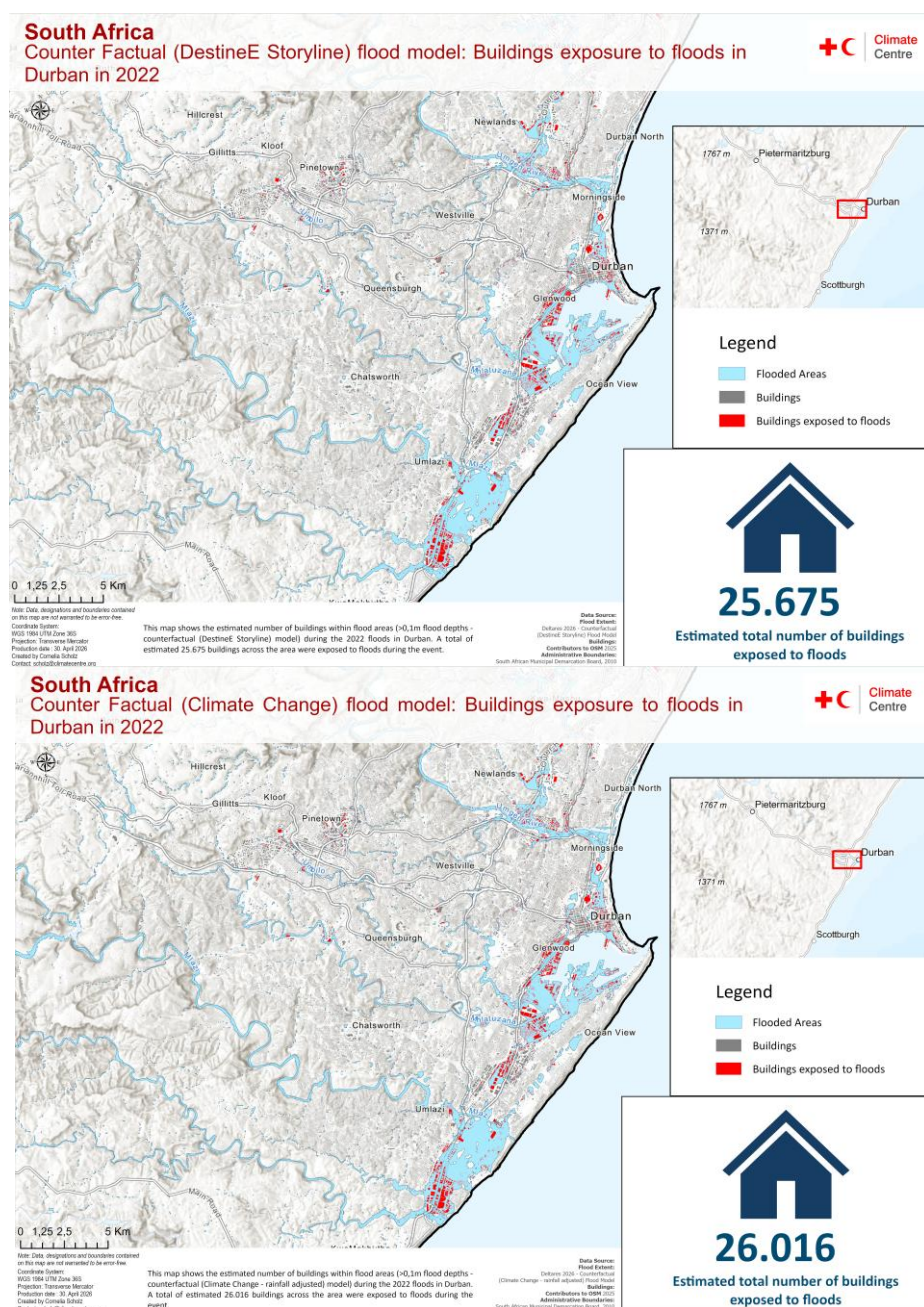


Figure 70: GIS based building exposure mapping for DestineE (upper panel) and CC (lower panel)

7.6.3. Stakeholder and policy relevance

This attribution analysis carries direct policy relevance for a range of actors involved in disaster risk management in eThekweni and KwaZulu-Natal municipalities, and the country more broadly. On the one hand, there is clear evidence for shifting resources to proactive risk reduction, rather than reactive responses in order to save lives and minimize damage. On the other hand, improving the communication and actionability of early warnings would have an equally important impact.

Looking at preventive risk reduction, the quantified climate-attributable increase in flood volume, extent, and depth strengthens the case for municipal authorities to upgrade stormwater infrastructure to standards that reflect current and future rainfall intensities. At the same time, national disaster management authorities which recognized the reactive orientation of flood response, can justify allocating resources for actions such as

drainage maintenance, catchment management, and stricter enforcement of settlement planning in floodplains and on high-risk slopes.

Turning to anticipatory action and early warnings, the finding that climate change disproportionately amplifies damage in already-identified hotspot areas, such as the Harbour and Southwest areas of Durban, gives municipal planners and humanitarian actors a spatially explicit basis for prioritising early warning coverage, retrofitting, and relocation or upgrading programmes in informal settlements, where vulnerability and exposure are highest. Finally, for meteorological services and community-based early warning initiatives, it is evident from this analysis given that climate change is shown to intensify the hazard itself, that improving the reach and clarity of warnings will be essential to save lives and reduce harm from future flooding events. Given the success of the community-based approach in one of the informal settlements, building on models such as this can complement national and municipal efforts.

8. Use Case 6: Crete Drought

8.1. Summary of event

The Tympaki use case is a system attribution study. It investigates the evolution of water resources in the Tympaki basin, located in southern Crete, Greece, during the period 1980–2022, and addresses the following question: "How have long-term changes in climate, land use and water management altered the state of the basin's water resources over four decades?"

The Tympaki study area comprises a drainage basin of approximately 265 km². The basin forms part of the wider Messara plain, the largest agricultural region in Crete and one of the island's most important food-producing areas. The study area consists of the lowland Tympaki plain in the west and the more elevated hills in the east. The basin is traversed by the Geropotamos River and its principal tributaries, including the Koutsoulidis and Mageiros streams.

According to the Water Framework Directive (WFD) typology, the basin includes seven river water bodies and six groundwater bodies, representing one of the most intensively exploited water systems on the island. Groundwater constitutes the primary water resource supporting agricultural production. The alluvial aquifers underlying the Tympaki plain exhibit considerably higher permeability, transmissivity and groundwater storage capacity than the surrounding hilly formations, making the plain the principal area for groundwater abstraction.

Land use is dominated by agriculture, accounting for approximately 40% of the total basin area and nearly 88% of the central Tympaki plain, where intensive irrigated cultivation is concentrated. The basin supports a permanent population of approximately 11,000 inhabitants, while seasonal agricultural activity further increases pressure on local water resources. Groundwater abstraction for irrigation is estimated at approximately 7.5 million m³ per year, supplying nearly 40 km² of irrigated agricultural land.

The basin has experienced long-standing pressures associated with groundwater overexploitation and recurrent drought conditions, resulting in increasing competition among agricultural, domestic and tourism water uses, as well as declining groundwater levels and nitrates pollution. Understanding the relative contribution of climatic changes, land use evolution and water management practices to these pressures is therefore essential for designing effective adaptation strategies. This forms the basis of the attribution analysis presented in this study.

To assess the drivers of these changes, a detailed water resources model was developed using the Water Evaluation and Planning System (WEAP21)¹¹⁴. The model simulates the hydrological behaviour and water allocation of the basin at monthly time steps and sub-catchment scale, representing surface water, groundwater, agricultural demand, domestic demand and water management infrastructure.

The baseline simulation reproduces the observed evolution of the water system between 1980 and 2022 and quantifies water availability, sectoral water demand, water supply and unmet demand. Counterfactual simulations were subsequently performed to isolate the contributions of climate change and land use change by comparing the factual period against alternative scenarios representing pre-1980 climatic conditions and historical land use. This enables an attribution assessment of the relative influence of climate variability, land use change and water management on the evolution of water scarcity in the basin.

8.2. Observed hazards

Unlike the other COMPASS use cases, which focus on individual extreme events, the Tympaki use case investigates the long-term evolution of hydroclimatic conditions affecting water resources over a 43-year period (1980–2022). The principal hazard is prolonged water scarcity resulting from the combined effects of recurrent meteorological droughts, increasing evapotranspiration rates, and highly variable precipitation. These hazards

¹¹⁴ <https://www.weap21.org/>

progressively reduce surface water availability and groundwater recharge, increasing pressure on the basin's water resources.

The analysis is based on monthly climate forcing data derived from the ERA5 reanalysis at 10 km spatial resolution, bias-corrected using observations from local meteorological stations for the period 1980–2008. These data provide a consistent representation of precipitation and temperature over the study period and constitute the climatic forcing of the WEAP21 water resources model.

8.2.1. Type of hazards

The primary hazard considered in this study is long-term hydroclimatic drought, characterised by persistent deficits in water availability rather than by isolated extreme events. The hazard is driven by:

- prolonged dry periods of below-average precipitation;
- increased evapotranspiration associated with higher temperatures;
- reduced groundwater recharge and surface water availability;
- seasonal water scarcity during the irrigation period.

These hydroclimatic pressures directly influence the availability of water resources within the basin and increase the likelihood of water shortages across domestic, tourism and agricultural sectors.

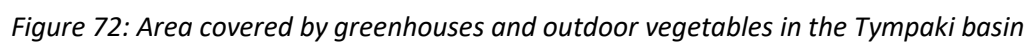
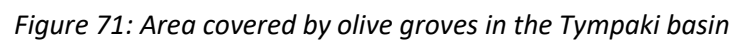
8.2.2. Form of compounding

Water scarcity in the Tympaki basin results from the interaction of multiple natural and anthropogenic drivers that reinforce one another over time.

On the climatic side, periods of reduced precipitation frequently coincide with elevated temperatures and increased evapotranspiration, reducing effective rainfall and groundwater recharge while simultaneously increasing irrigation requirements.

These climatic pressures are compounded by socio-economic drivers. Agriculture represents the dominant water-consuming sector in the basin, while seasonal tourism substantially increases domestic water demand during the dry summer months, when water resources are already under maximum stress. Changes in land use and irrigation expansion further increase water demand and modify the spatial distribution of abstractions.

Consequently, water scarcity emerges as the cumulative result of interacting climatic variability, land use change and increasing water demand, rather than from any single drought episode.



8.2.3. Driving dynamics

The Tympaki basin, located in southern Crete, experiences a typical Mediterranean climate, characterised by cool winters and hot, dry summers. Annual precipitation is approximately 750 mm (average of the period 1980-2022) concentrated between October and March, while water demand peaks during the summer irrigation season when natural water availability is at its lowest.

Land use and agricultural practices are major drivers of water demand within the basin. Agriculture is the dominant land use, accounting for approximately 40% of the total basin area, and represents by far the largest water-consuming sector. Olive groves are the predominant crop, covering approximately 7,800 hectares (78 km²), of which around 3,300 hectares (33 km²) are irrigated. Intensive horticulture further increases water demand, with approximately 350 hectares of greenhouses and 100 hectares of outdoor vegetable cultivation. Consequently, irrigation requirements are highly seasonal and closely linked to climatic conditions, making agricultural water demand particularly sensitive to prolonged periods of reduced precipitation and increased atmospheric evaporative demand.

Water resources are supplied by local groundwater aquifers, the Faneromeni Reservoir and external inflows from the neighbouring Geropotamos catchment. The Faneromeni Reservoir, commissioned in 2005, has a storage capacity of approximately 20 million m³ and was constructed to support irrigation across the wider Messara plain, including the Tympaki basin. Approximately 3 million m³ of water are supplied annually from the reservoir to the central Tympaki plain. However, despite this additional resource, irrigation water demands are not fully satisfied in dry years, and unmet demands continue to occur, highlighting the persistent imbalance between water availability and water demand.

To represent these interactions, a detailed water resources management model was developed in WEAP21 using a node-based architecture consisting of 3 sub-catchments, 7 groundwater aquifers, 1 reservoir and 26 demand sites representing urban, agricultural and tourism water users. This model was developed in the framework of the EU funded project TRANSCEND^{115, 116} and was utilized here for the purposes of this COMPASS Use Case. Water allocation follows predefined operational priorities, with domestic water supply receiving the highest priority, followed by agricultural demands subject to irrigation quotas and the operational rules of the Faneromeni Reservoir. This modelling framework enables the assessment of how climate variability, land use and water management interact to influence water availability and water allocation across the basin.

8.2.4. Intensity/Extremity/Magnitude

Rather than being characterised by a single extreme event, the magnitude of the hazard is assessed through the long-term evolution of hydroclimatic conditions over the period 1980–2022. The 43-year record captures substantial interannual variability, with alternating wet and dry periods that directly influence groundwater recharge, reservoir inflows and the availability of water resources across the basin.

Annual precipitation exhibits considerable variability, ranging from a minimum of 326 mm (observed in 1990) to a maximum of 1,084 mm (observed in 2019), with a long-term mean of 747 mm and a standard deviation of 175 mm (Table 8). This corresponds to a coefficient of variation of approximately 23%, highlighting the naturally high variability of the Mediterranean climate. Such variability results in large year-to-year differences in the volume of renewable water resources available to satisfy agricultural, domestic and tourism demands. In contrast, annual potential evapotranspiration (PET) remains consistently high throughout the study period. Annual PET

¹¹⁵ <https://transcendresearchproject.com/>

¹¹⁶ Cinzia Alessandrini, Safa Baccour, Omar Cenobio-Cruz, Giuliano Di Baldassarre, Camilo Gonzalez, Osama Hassan, Maggie Kossida, Marinos Kritsotakis, Stella Mavraki, Majid Niazkar, Fotios Pantazoglou, Adrià Rubio Martín, Haniyeh Salmani, Francesco Sapino, Tania Santos, Giammauro Soriano, Ioannis Tsoukalas (2026). *Database of plausible futures by lab and sourcebook*. Deliverable D3.3 Transcend project.

ranges from 1,277 mm to 1,414 mm, with a long-term mean of 1,337 mm and a standard deviation of only 33 mm, corresponding to a coefficient of variation of approximately 2.5%. This indicates that the atmospheric demand for water is persistently high and varies only marginally from year to year compared with precipitation.

The combined evolution of precipitation and PET (Figure) highlights that annual PET exceeds precipitation throughout the entire study period. On average, annual precipitation supplies only around 56% of the atmospheric evaporative demand (747 mm compared with 1,337 mm PET). The basin naturally experiences a chronic water deficit, making irrigated agriculture heavily dependent on groundwater abstractions and reservoir storage. During drought years, precipitation declines substantially while PET remains close to its long-term average. This combination widens the climatic water deficit, reducing groundwater recharge and surface water availability while simultaneously increasing crop water requirements. As a result, prolonged periods of below-average precipitation have a disproportionate impact on water resources because they occur under persistently high atmospheric evaporative demand.

Table 8: Summary statistics of annual precipitation and potential evapotranspiration (PET) for the period 1980-2022.

	Annual Precipitation (mm)	Annual PET (mm)
Period	1980-2022	1980-2022
Number of years	43	43
Mean	747	1,337
Median	753	1,336
Standard Deviation	175	33
Minimum	326 (in 1990)	1,277 (in 1997)
Maximum	1,084 (in 2019)	1,414 (in 2010)

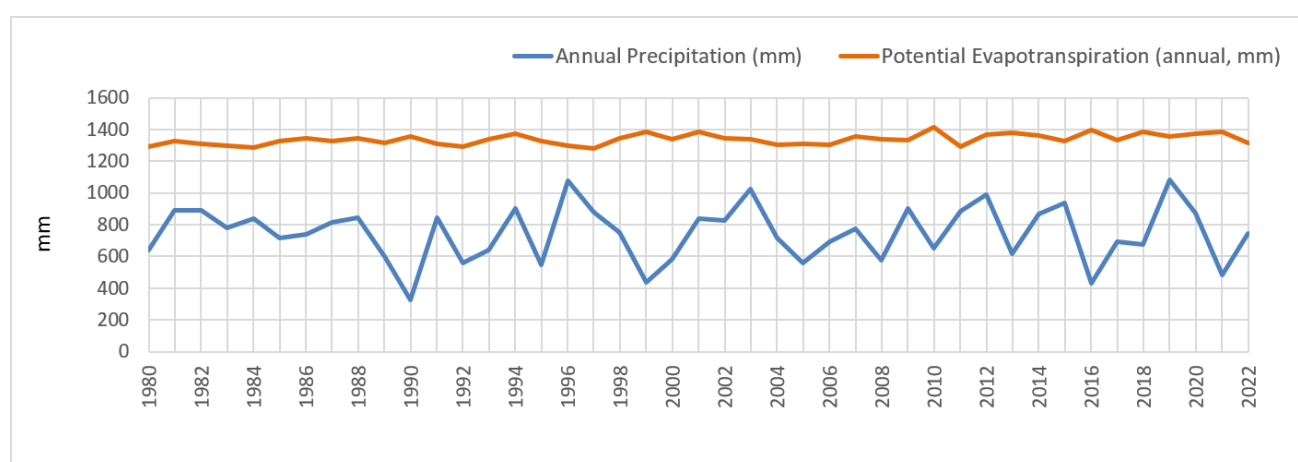


Figure 73: Annual areal precipitation and potential evapotranspiration for the period 1980-2022 (ERA-5 bias-corrected data)

To characterise meteorological drought conditions, the 12-month Standardised Precipitation Index (SPI-12) was calculated for the entire study period. Approximately 69% of all months were classified as near-normal conditions ($-1 \leq \text{SPI} \leq 1$), while 17% of months experienced moderate to extreme drought conditions ($\text{SPI} \leq -1$)

indicating that sustained dry conditions constitute a significant component of the basin's hydroclimatic variability. In comparison, 14% of months were classified as moderately to extremely wet ($SPI \geq 1$).

Table 9: Classification of SPI-12 values for the period 1980–2022.

Range of SPI values	Precipitation class	Count (months)	% of months within the period 1980-2022
$SPI \leq -2.0$	Extremely dry	14	3%
$-2.0 < SPI \leq -1.5$	Severely dry	38	7%
$-1.5 < SPI \leq -1.0$	Moderately dry	37	7%
$-1.0 < SPI \leq 1.0$	Near normal	358	69%
$1.0 < SPI \leq 1.5$	Moderately wet	34	7%
$1.5 < SPI \leq 2.0$	Severely wet	21	4%
$2.0 < SPI$	Extremely wet	14	3%

Based on the SPI-12 analysis, a total of 13 drought events occurred in the Tympaki basin during the period 1980–2022. A drought event was defined as a continuous period with SPI values below zero that reached at least $SPI = -1.0$ before terminating when SPI became positive again. The cumulative magnitude of each drought event was calculated as the sum of the absolute SPI values over all months belonging to the event, thereby accounting for both the duration and severity of the drought. Drought events ranged in duration from 2 to 34 months and in cumulative magnitude from 1.3 to 42, illustrating the substantial variability in both the persistence and severity of meteorological droughts affecting the basin. The most significant events are summarised in Table 10. The longest and most severe drought occurred between 1989 and 1991, lasting 34 months and reaching a cumulative magnitude of 42. Two additional prolonged droughts occurred during 1999–2001 and 2016–2018, each lasting 28 months, with cumulative magnitudes of 35 and 29, respectively. The four longest droughts (1989–1991, 1999–2001, 2004–2006 and 2016–2018) account for approximately 65% of the total cumulative drought magnitude recorded during the study period, demonstrating that the hydroclimatic hazard is dominated by the prolonged drought episodes rather than by many short, isolated events. These prolonged events are expected to have substantially reduced groundwater recharge and surface water availability while increasing irrigation requirements, thereby placing sustained pressure on the basin's water resources.

Table 10: Major drought events identified in the Tympaki basin during 1980–2022, showing event duration and cumulative drought magnitude

Years	Duration (months)	Drought magnitude
1989-1991	34	42
1999-2001	28	35
2016-2018	28	29
2004-2006	21	19
2016	7	15
1986	12	14
1993	14	9
2013	14	8
2006-2007	13	6

Overall, the hydroclimatic hazard affecting the Tympaki basin is not defined by isolated drought events but by the cumulative effects of recurrent precipitation deficits occurring within a climate characterised by persistently high atmospheric evaporative demand. Together, these conditions create chronic water stress, which is further amplified by intensive agricultural water use and forms the basis for the attribution analysis presented in this study.

8.3. Observed impacts

The recurrent meteorological droughts described in Section 8.2 have resulted in sustained pressure on the water resources of the Tympaki basin. Due to the basin's strong dependence on irrigated agriculture and groundwater abstractions, prolonged periods of below-average precipitation translate into reduced groundwater recharge, declining water availability and increasing competition for limited water resources. Salinization and seawater intrusion have also been observed in one of the groundwater bodies, namely the porous coastal system *EL1300082*. The observed impacts extend beyond individual drought years and reflect the cumulative effects of long-term hydroclimatic variability combined with growing water demands.

8.3.1. Quantitative impacts

The quantitative impacts of drought are assessed through a range of hydrological and water management indicators simulated by the WEAP21 water resources model for the period 1980-2022. These indicators describe both the availability of water resources and the extent to which sectoral water demands can be satisfied under observed climatic conditions.

The principal indicators considered include:

- inflows and outflows to the basin (Figure);
- streamflow at each sub-catchment (Figure);
- irrigation, domestic and tourism water demands (Figure , Figure);
- unmet water demand per demand site, particularly for irrigation (Figure , Figure).

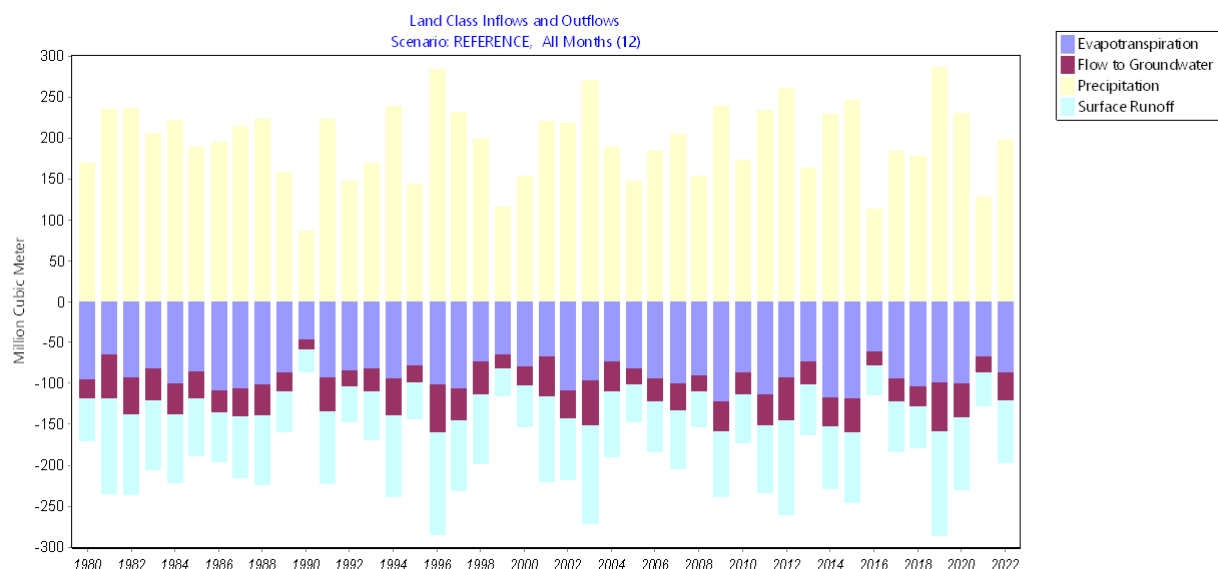


Figure 74: Inflows and outflows in the Tympaki basin for the period 1980-2022.

Deliverable 4.2 – Hazard and Impact Synthesis and Attribution for Phase II use case

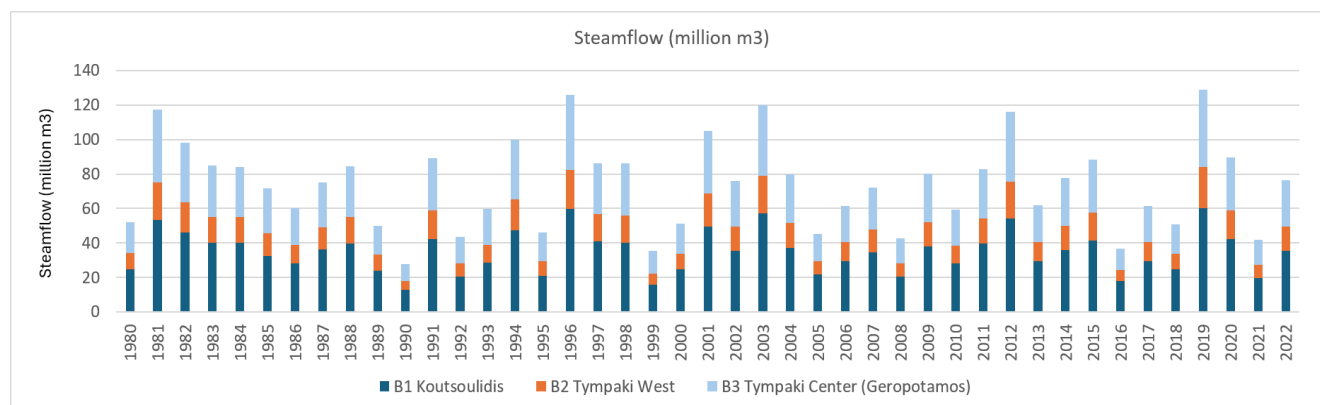


Figure 75: Streamflows in the Tympaki basin sub-catchments (1980–2022).

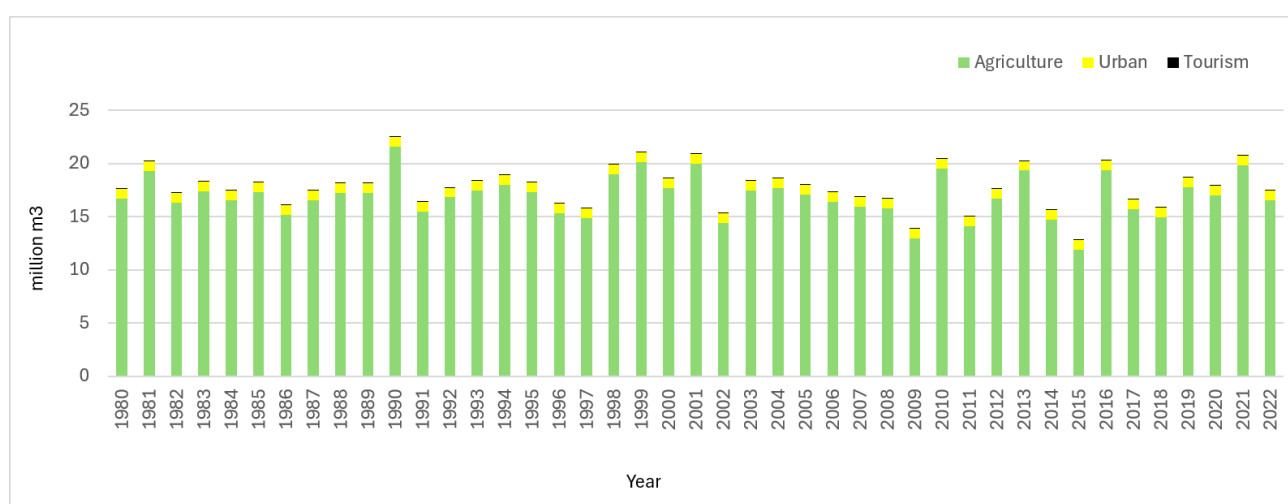


Figure 76: Simulated total annual water demand (1980–2022) per sector.

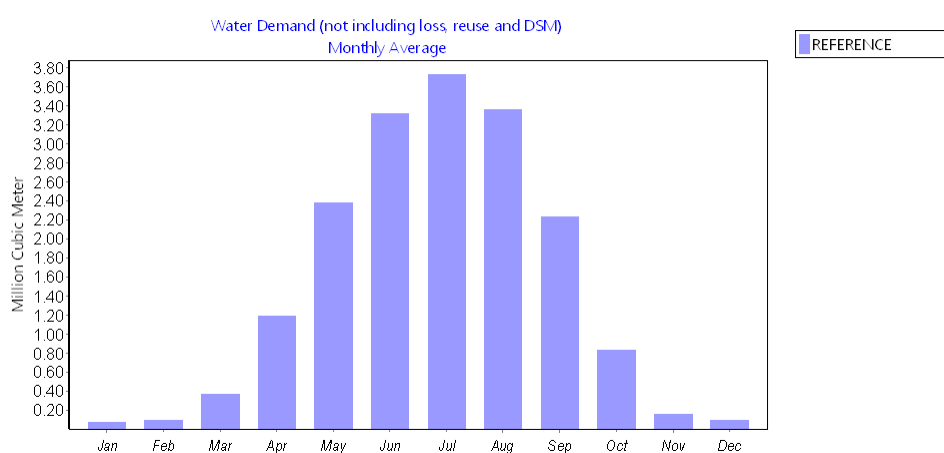


Figure 77: Distribution of mean monthly water demand (1980–2022).

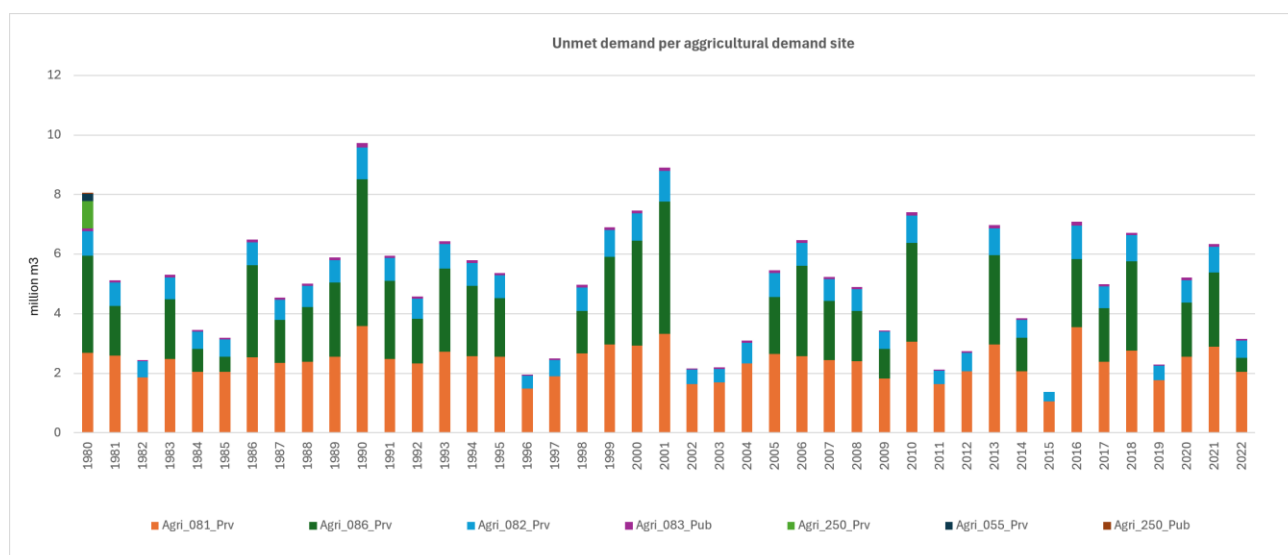


Figure 78: Simulated total annual unmet water demand (1980–2022) per agricultural demand site.

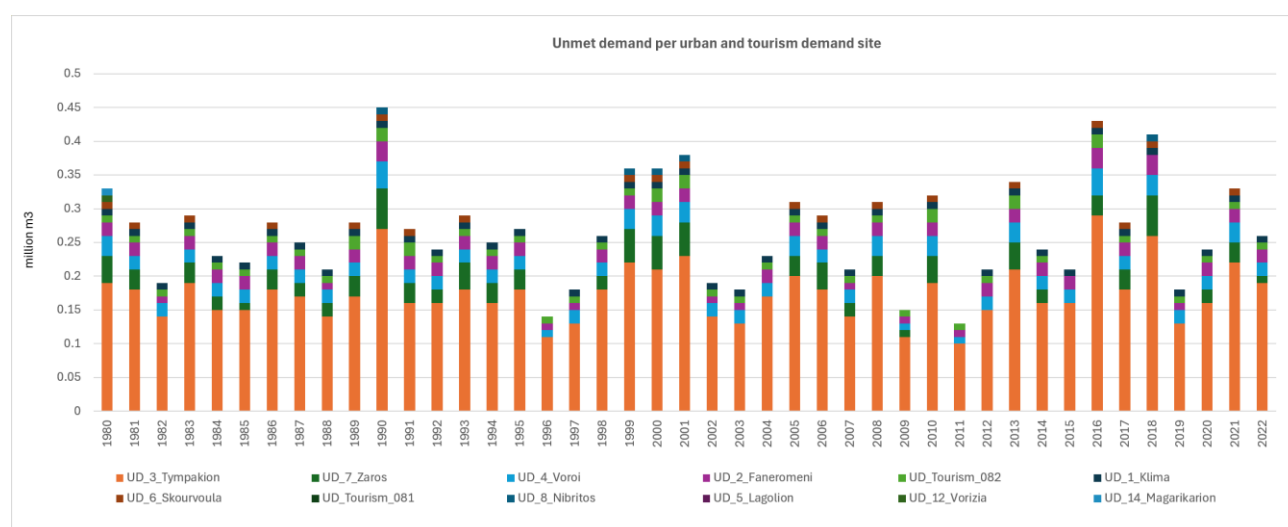


Figure 79: Simulated total annual unmet water demand (1980–2022) per urban and tourism demand site.

Summary statistics of the key indicators, along with the observed impacts during dry years are presented below in Table 11. The mean annual water demand amounts to 17.88 million m³, of which about 95% (~17 million m³) is for agriculture, about 5% (0.91 million m³) for the urban sector and 0.1% (0.02 million m³) for tourism. The available water supply cannot meet these demands, resulting in unmet demand every year. On average, 29% (about 5.23 million m³) of the demands cannot be met, mainly in the agricultural sector. However, 10% (or 0.09 million m³) of the urban and tourism water demand cannot be met on average.

During prolonged drought periods, reduced precipitation and groundwater recharge lead to declining groundwater availability and lower surface water resources. At the same time, irrigation requirements increase due to the persistent atmospheric evaporative demand, resulting in higher abstraction pressures and increasing unmet water demand. The temporal evolution of these indicators provides a quantitative assessment of the impacts of hydroclimatic drought on the Tympaki water resources system and forms the basis for the attribution analysis presented in subsequent sections.

Table 11: Summary statistics of key indicators (all units in million m³)

	Mean annual	Median	Standard Deviation	Maximum	Minimum	Observed impact during dry years
Precipitation	197.86	199.33	46.38	286.87 (in 2019)	86.30 (in 1990)	Reduction in the range of 7% to 56% (e.g. in 1990, 2016, 1999, 2021, 2005)
Evapotranspiration	89.89	92.79	16.67	121.91 (in 2009)	46.03 (in 1990)	Reduction in the range of 9% to 49% (e.g. in 1990, 2016, 1999, 2021, 2001)
Surface runoff	74.02	75.88	25.80	128.83 (in 2019)	27.66 (in 1990)	Reduction in the range of 16% to 63% (e.g. in 1990, 1999, 2016, 2021, 2008)
Flow to groundwater	33.95	34.72	11.81	59.00 (in 2019)	12.62 (in 1990)	Reduction in the range of 16% to 63% (e.g. in 1990, 1999, 2016, 2021, 2008)
Water demand	17.88	17.95	1.98	22.50 (in 1990)	12.82 (in 2015)	Increase by 6% to 26% (e.g. in 1990, 1999, 2001, 2021, 2010, 2016)
Supply required (including losses)	19.77	19.85	2.20	24.90 (in 1990)	14.15 (in 2015)	Increase by 6% to 26% (e.g. in 1990, 1999, 2001, 2021, 2010, 2016)
Supply delivered	14.53	14.65	1.85	18.19 (in 2019)	10.43 (in 2018)	Decreased by 4% to 28% (e.g. 2017-2018, 2005-2009, 1989-91, 1999-2001, 1986, 1993, 2014-2015)
Unmet demand	5.23	5.40	2.10	10.18 (in 1990)	1.57 (in 2015)	Increase by 36% to 95% (e.g. 1990, 2001, 2000, 2010, 2016, 2013, 1999, 2018)
Unmet demand as % of water demand	29%	31%	10%	48% (in 1990)	12% (in 2015)	Increase by 17% to 64% (e.g. 1990, 2018, 2001, 2000, 1986, 2006, 1991, 2010, 2016)
Unmet demand for agriculture	4.96	5.13	2.03	9.73 (in 1990)	1.37 (in 2015)	Increase by 30% to 96% (e.g. 1990, 2001, 2000, 2010, 2016, 2013, 1999, 2018)
Unmet demand for urban + tourism	0.09	0.09	0.04	0.18 (in 1990)	0.03 (in 1996)	Increase by 22% to 100% (e.g. 1990, 2000, 2001, 2018, 1999, 2016, 2010)

8.3.2. Qualitative impacts and responses

Beyond the quantitative changes in water availability, recurrent droughts have produced a range of wider impacts on the chemical status of groundwater bodies, water management and agricultural production within the Tympaki basin. Agriculture, which represents the dominant water user, is particularly vulnerable to prolonged water shortages because crop production depends heavily on irrigation throughout the dry season. Reduced production has an impact on farmers' income.

To mitigate these impacts, water resources are managed through an integrated system comprising groundwater abstractions, surface water resources and releases from the Faneromeni Reservoir. Water allocation follows predefined priorities that seek to satisfy domestic water requirements while maximising the reliability of irrigation supplies. Nevertheless, during prolonged droughts the available resources are insufficient to fully satisfy agricultural demand, resulting in water deficits and increased pressure on groundwater resources.

Over recent decades, these recurring drought conditions have reinforced the importance of adaptive water management, including the development of reservoir infrastructure (plans for the diversion of Platis stream into the Faneromeni reservoir), regulated groundwater abstractions and improved allocation strategies. However, the persistence of unmet irrigation demand during severe drought episodes indicates that the basin remains vulnerable to sustained reductions in water availability.

The observed impacts and management responses described above provide the foundation for the attribution analysis undertaken in this study, which quantifies the relative contributions of climate variability, land-use change and water management interventions to the evolution of water scarcity in the Tympaki basin.

8.4. Modeling framework

The attribution analysis is based on an integrated modelling framework that combines hydroclimatic drought characterisation with physically-based water resources simulation. Meteorological drought conditions were first identified using the Standardised Precipitation Index (SPI), while the impacts of drought on water availability, water allocation and water shortages were simulated using the Water Evaluation and Planning (WEAP21) system. The modelling framework enables the assessment of historical drought impacts during the period 1980–2022, as well as the evaluation of counterfactual climate, land-use and prolonged drought scenarios.

8.4.1. Hazard modeling

Hydroclimatic drought conditions were characterised using the 12-month Standardised Precipitation Index (SPI-12) following the methodology proposed by McKee et al. (1993)¹¹⁷ and subsequently standardised by the World Meteorological Organization¹¹⁸. SPI expresses accumulated precipitation anomalies relative to the long-term climatological record as standard deviations from the mean, with positive values indicating wetter-than-normal conditions and negative values indicating drier-than-normal conditions.

Monthly precipitation totals were aggregated into rolling 12-month accumulations (SPI-12), and separate Gamma probability distributions were fitted for each calendar month using the common climatological reference period 1950–2022. The cumulative probability of each observed precipitation accumulation was calculated from the fitted Gamma distribution, incorporating the probability of zero precipitation where applicable, and subsequently transformed to the corresponding standard normal variate to obtain the SPI values, which have a mean of zero and a standard deviation of one.

Drought events were defined as continuous periods during which SPI remained below zero and reached at least SPI = -1.0, terminating when SPI became positive again. For each event, the duration, minimum SPI value and cumulative drought magnitude were calculated to characterise the persistence and severity of meteorological droughts affecting the Tympaki basin.

In addition to the historical drought analysis, two synthetic prolonged drought scenarios were developed to assess the drought hazards and the resilience of the basin under sustained hydroclimatic stress. These scenarios represent five-year and seven-year consecutive drought events generated from the historical climate record using stochastic climate realisations that preserve the statistical characteristics of the observed precipitation series. The synthetic climate series were subsequently used as climatic forcing within the WEAP model to

¹¹⁷ McKee, T. B., Doesken, N. J., & Kleist, J. (1993). *The Relationship of Drought Frequency and Duration to Time Scales*. Proceedings of the Eighth Conference on Applied Climatology, American Meteorological Society, Anaheim, California, USA, 179–184. <https://www.scirp.org/reference/ReferencesPapers?ReferenceID=2099290>

¹¹⁸ World Meteorological Organization (WMO). (2012). *Standardized Precipitation Index User Guide*. WMO-No. 1090. Geneva, Switzerland. <https://library.wmo.int/viewer/39629#page=3&viewer=picture&o=bookmarks&n=0&q=>

evaluate the response of the water resources system under prolonged drought conditions exceeding those observed during the historical period.

8.4.2. Impact modeling

The impacts of hydroclimatic drought were simulated using the Water Evaluation and Planning (WEAP21) system, an integrated water resources modelling platform that represents the coupled interactions between hydrology, water demands and water management infrastructure. The model was developed at a monthly time step for the period 1980–2022 using a detailed node-based representation of the Tympaki basin, comprising 3 sub-catchments, 7 groundwater aquifers, 1 reservoir and 26 demand sites representing urban, agricultural and tourism water users.

Historical precipitation and temperature data were obtained from the ERA5 reanalysis at 10 km spatial resolution and bias-corrected using observations from local meteorological stations for the period 1980–2008. Agricultural water demands were derived from detailed land-use and irrigation datasets provided by OPEKEPE and the Local Land Reclamation Organisation (TOEB A'), while domestic and tourism demands were estimated using per-capita consumption values of 220 L person⁻¹ day⁻¹ and 350 L person⁻¹ day⁻¹, respectively, consistent with the latest River Basin Management Plan for Crete.

The WEAP model explicitly simulates the principal hydrological and management processes governing the basin, including groundwater recharge, groundwater storage, river flows, reservoir storage, groundwater abstractions, water allocation, water supplied and unmet demand. Water allocation follows predefined operating priorities, whereby domestic water supply receives the highest priority, followed by tourism and agricultural demands, while respecting irrigation quotas and the operational rules of the Faneromeni Reservoir.

The model was used to simulate both the historical baseline conditions (1980–2022) and the various counterfactual scenarios, enabling the quantification of changes in water availability, water demand and water shortages attributable to climate variability, land-use change and prolonged drought conditions.

Exposure mapping

Exposure is represented by the spatial distribution and magnitude of water demands across the Tympaki basin. The model includes 26 demand nodes representing the agricultural, domestic and tourism sectors.

Agricultural nodes' exposure is determined from the crop type, the spatial distribution of irrigated crops and associated irrigation requirements, and the connection (or not) to the public water supply network (Figure). Farmers that are not connected to the public water supply system and use private boreholes are more prone to water shortages. As a result, the agricultural nodes with the highest exposures are the nodes supplied via private boreholes located in the crop-intensive areas of EL300081, EL300082, EL300086 (Figure), namely Agri_081_Priv (average annual demand 2.94 mio m³), Agri_082_Priv (average annual demand 0.93 mio m³), Agri_086_Priv (average annual demand 4.95 mio m³).

Domestic and tourism demands are represented using population-based consumption estimates and exposure is determined by the water supply source and infrastructure serving that population. The urban and tourism nodes with the highest exposures are the nodes supplied by the highly exploited aquifers EL300081, EL300082, EL300086 (Figure), namely UD_3_Tympakion, UD_7_Zaros, UD_4_Voroi, UD_2_Faneromeni and UD_Tourism_082.

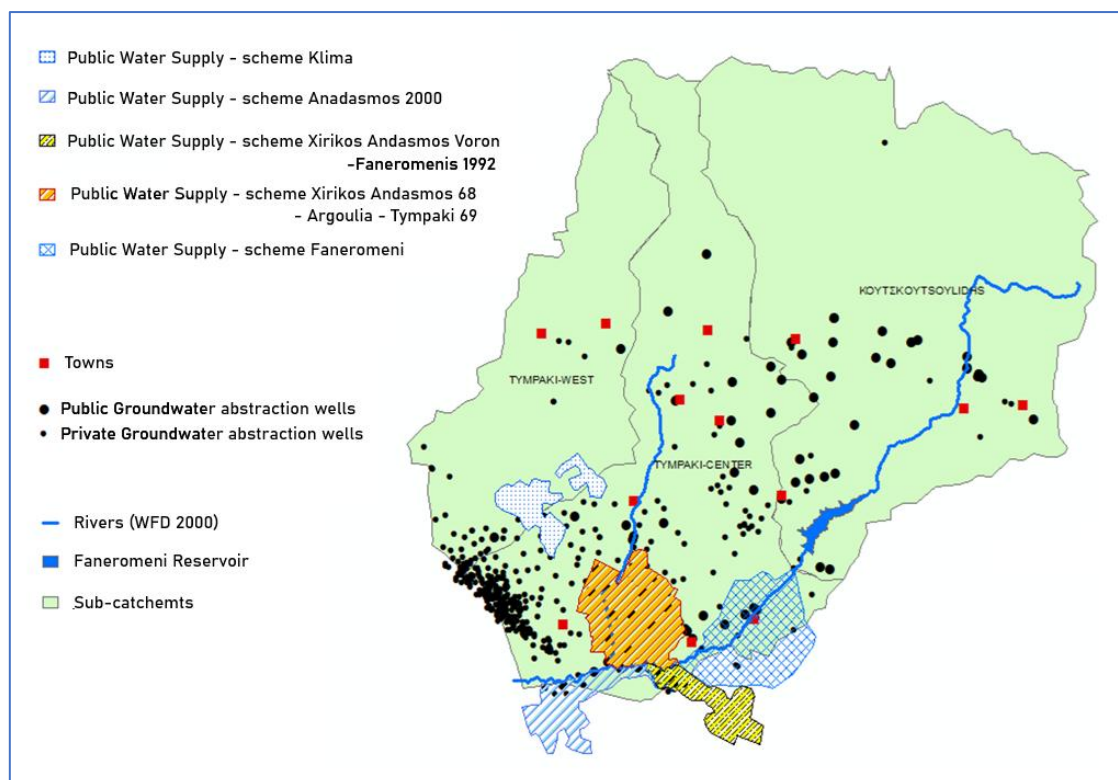


Figure 80: Areas covered by public water supply irrigation schemes and location of private groundwater abstraction wells.

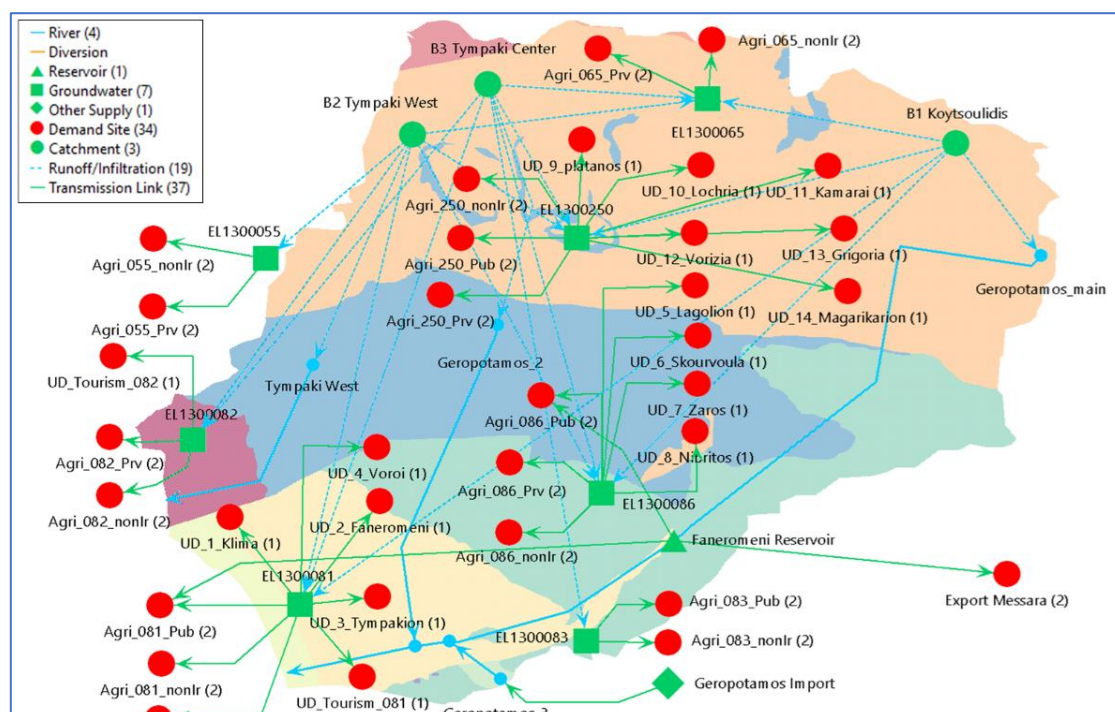


Figure 81: WEAP model scheme and groundwater bodies in the Tympaki basin

Unlike conventional natural hazard models, where vulnerability is represented through explicit damage functions, vulnerability within the Tympaki modelling framework is represented implicitly through the structure and operational rules of the water resources system. The response of each demand sector to hydroclimatic stress depends on water availability (which directly influences the supply delivered), water allocation priorities, groundwater abstraction capacity, reservoir storage, and the operational rules governing the Faneromeni Reservoir. These factors determine the extent to which reductions in water availability propagate into water shortages across competing users.

The vulnerability of each demand sector depends on the availability of water resources (which directly influences the supply delivered), the capacity of the supply infrastructure, groundwater abstraction potential, reservoir storage, water allocation priorities and the operational rules governing the Faneromeni Reservoir. Together, these factors determine the ability of the system to satisfy competing water demands under drought conditions and therefore control how reductions in water availability propagate into water shortages. Consequently, simulated unmet water demand (Figure and Figure) represents the principal indicator of system vulnerability, reflecting the combined influence of climatic conditions, infrastructure capacity and water management practices.

The performance of the system is evaluated using **water supply reliability** and **unmet water demand**. Water supply reliability expresses the percent of time in which the demand of a site was fully satisfied. For example, if a demand site has unmet demands (deficit) in 6 years out of a 10-year scenario, the reliability would be $(10-6) / 10 = 40\%$. Unmet demand quantifies the volume of water that cannot be delivered because of resource limitations or operational constraints. Together, these indicators provide an integrated measure of the vulnerability of each demand sector to hydroclimatic drought.

Figure and Figure illustrate the simulated water supply reliability for the agricultural, urban and tourism demand nodes during the historical period (1980–2022).

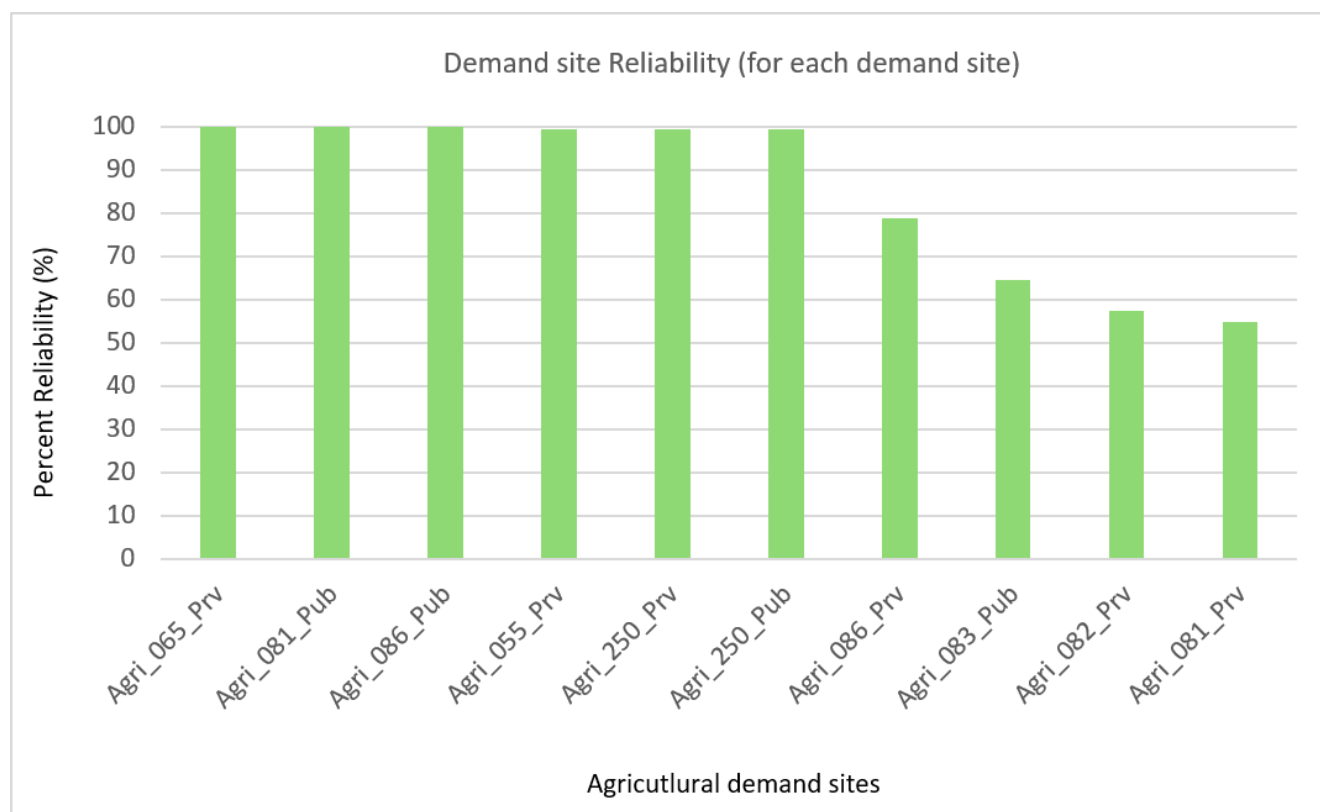


Figure 82: Water supply reliability for the agricultural sector, per demand node (1980–2022).

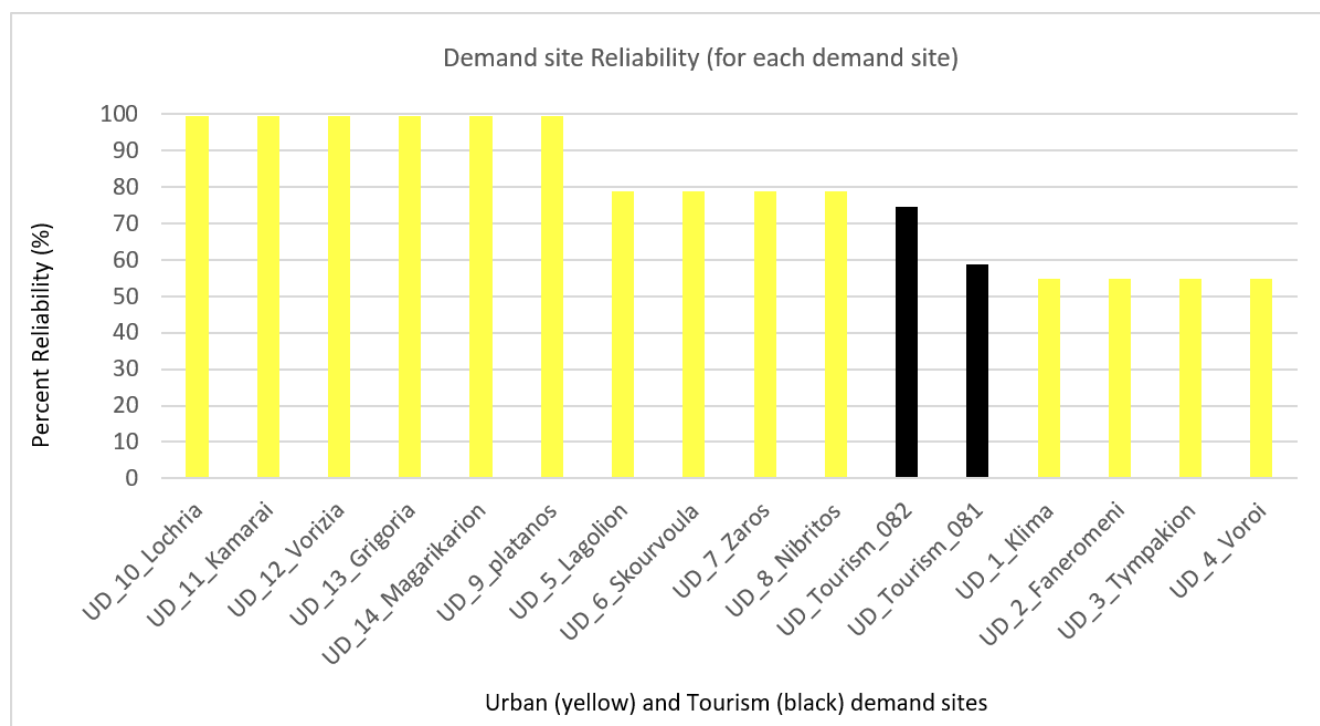


Figure 83: Water supply reliability for the urban and tourism sectors, per demand node (1980-2022).

Table 12 summarizes the water supply reliability across all sectors. It provides also their classification under different reliability classes, defined as very high (>95%), high (80-95%), medium (60-80%), low (40-60%), and very low (<40%). It is observed that out of the 10 agricultural demand sites, 2 have medium irrigation water supply reliability and another 2 have low. Regarding the urban and tourism sector, 6 demand sites have very high reliability, while 5 have medium and another 5 have low. Finally, the 2 nodes of tourism water demand fall within medium and low reliability classes. It should be noted however that the annual water deficits in the urban and tourism nodes are on average 0.01- 0.15 mio m³, whereas in the agricultural sector these are much higher, on average 0.1 – 2.4 mio m³ in the different demand nodes.

Table 12: Water supply reliability classifications for sectors in the Tympaki basin for the period 1980-2022. Reliability is defined as the percentage of time in which the demand of a site was fully satisfied.

Reliability class	Agricultural demand nodes	Urban + Tourism demand nodes
Very High (> 95%)	6	6
High (80% - 95%)	-	-
Medium (60% - 80%)	2	5
Low (40% - 60%)	2	5
Very Low (< 40%)	-	-

8.5. Attribution modeling framework

8.5.1. Event definition

The Tympaki use case is not focusing on an individual extreme event but rather considers the long-term evolution of hydroclimatic water scarcity as the event of interest. The attribution baseline period extends from 1951 to 1970, during which the basin experienced multiple drought episodes, and compares it to the next period 1980–2022 by which time substantial changes in land use and water management had led to increasing water demands and groundwater over-exploitation. The attribution analysis therefore seeks to explain the observed evolution of the water resources system over this period rather than the impacts of a single drought event. The principal impact indicators considered include water availability, water supplied and unmet water demand. Changes in these indicators between the factual and counterfactual simulations provide a quantitative measure of the influence of the investigated drivers on the evolution of water scarcity.

8.5.2. Factual and counterfactual simulations

The attribution analysis is based on comparisons between a factual simulation representing the observed evolution of the basin and a series of counterfactual simulations representing alternative but plausible historical conditions of the period 1951–1970. The factual simulation reproduces the observed period (1980–2022) using the historical climate record, observed land use, existing water management infrastructure and current operating rules. This simulation represents the best estimate of the historical evolution of the Tympaki water resources system.

Two principal counterfactual scenarios were developed:

Climate counterfactual. This scenario replaces the observed climatic forcing with a synthetic climate representative of pre-1980 conditions, namely the period 1951–1970, while maintaining the observed land use, water demands and management practices. The objective is to isolate the contribution of climatic changes in the evolution of water availability and water scarcity. The climate counterfactual 1950–1970 was developed using the ATTRICI (ATTRIButing Climate Impacts)¹¹⁹ model to detrend the observational (factual) ERA5 climatic data of the period 1951–1970. This involved removing the long-term changes correlated with global mean temperature shifts while preserving internal daily weather variability.

A key strength of the ATTRICI approach for this use case is that it generates a counterfactual climate that remains closely linked to the observed meteorological record. By removing the component of climatic change associated with changes in global mean temperature while retaining the internal temporal variability of the observed weather, the approach preserves the sequencing and variability of wet and dry conditions that are important for simulating groundwater recharge, irrigation requirements, water balance and water shortages in the WEAP models. This makes it particularly suitable for attribution analysis, as factual and counterfactual simulations can be compared while limiting changes to the climate signal of interest. The approach nevertheless relies on important assumptions. In particular, it assumes that the relationship used to remove the climate-change signal provides an adequate representation of how the relevant climatic variables would have evolved in the absence of the observed long-term warming. The counterfactual therefore represents a modelled “world without the attributed climate trend”, rather than a reconstruction of the climate that would actually have occurred. Moreover, because the observed temporal variability is retained, individual drought sequences remain closely related to those of the factual climate. The resulting attribution should consequently be interpreted as the estimated effect of the removed long-term climate signal on water-resource impacts, conditional on the ATTRICI

¹¹⁹ Mengel, M., Treu, S., Lange, S., and Frieler, K. (2021). *ATTRICI v1.1 – counterfactual climate for impact attribution*. Geosci. Model Dev., 14, 5269–5284, <https://doi.org/10.5194/gmd-14-5269-2021>

methodology and the WEAP model assumptions, rather than as an estimate of the full range of possible counterfactual drought conditions.

Land-use counterfactual. This scenario represents historical land-use conditions characteristic of the period prior to the expansion of irrigated agriculture while maintaining the observed climatic forcing. More specifically, the land-use counterfactual considers the following changes for the period 1950-1970:

- no public irrigation supply schemes existed in the basin (i.e. the ones illustrated in Figure); thus the olive groves that are currently irrigated via these systems were not irrigated in the pre-1970 period;
- the outdoor vegetables were irrigated solely by private groundwater wells;
- no greenhouses existed in the pre-1970 period;
- the olive trees that are irrigated via private boreholes were approximately 30% fewer in number;
- the Faneromeni reservoir was not constructed; thus this surface water supply did not exist;
- the urban water demand was set to 120 lt/cap/day;
- there is no tourism water demand.

Differences between the factual and counterfactual simulations are evaluated against the indicators used previously in section 8.3.1, namely inflows and outflows to the basin, streamflow, water demand and unmet demand per sector and node, and water supply reliability. Together, these comparisons provide a quantitative assessment of the relative influence of climate change, land-use change and water management on the long-term evolution of water scarcity in the Tympaki basin.

8.6. Results

8.6.1. Factual hazards and impacts

The results demonstrate that the basin is characterised by recurrent drought episodes, high interannual variability in precipitation and persistently high atmospheric evaporative demand, resulting in chronic pressure on available water resources. Overall, the historical simulation 1951-1970 (based on the ERA5 factual data) re-confirms that water scarcity in the Tympaki basin is not associated with isolated drought events but results from the cumulative effects of recurrent hydroclimatic droughts acting upon a highly water-demanding agricultural system. The mean annual precipitation and PET for the 1950-1970 period, based on the ERA5 factual data (Table 13) are very similar to those observed during 1980-2022, being only 2% and 1% lower, respectively. The resulting unmet demand remains at the same levels it was in the 1980-2022 if we retain the same land uses. The same observations apply even if we use the ATTRICI counterfactual 1950-1970 data. This means that the influence of the climate is not the dominant factor.

Table 13: Summary statistics of annual precipitation and potential evapotranspiration (PET) for the period 1950-1970 (based on the ERA5 factual data).

	Annual Precipitation (mm)	Annual PET (mm)
Period	1950-1970	1950-1970
Number of years	21	21
Mean	732	1,324
Median	741	1,316
Standard Deviation	173	23
Minimum	417 (in 1959)	1,285 (in 1964)

Maximum	1,011 (in 1968)	1,373 (in 1955)
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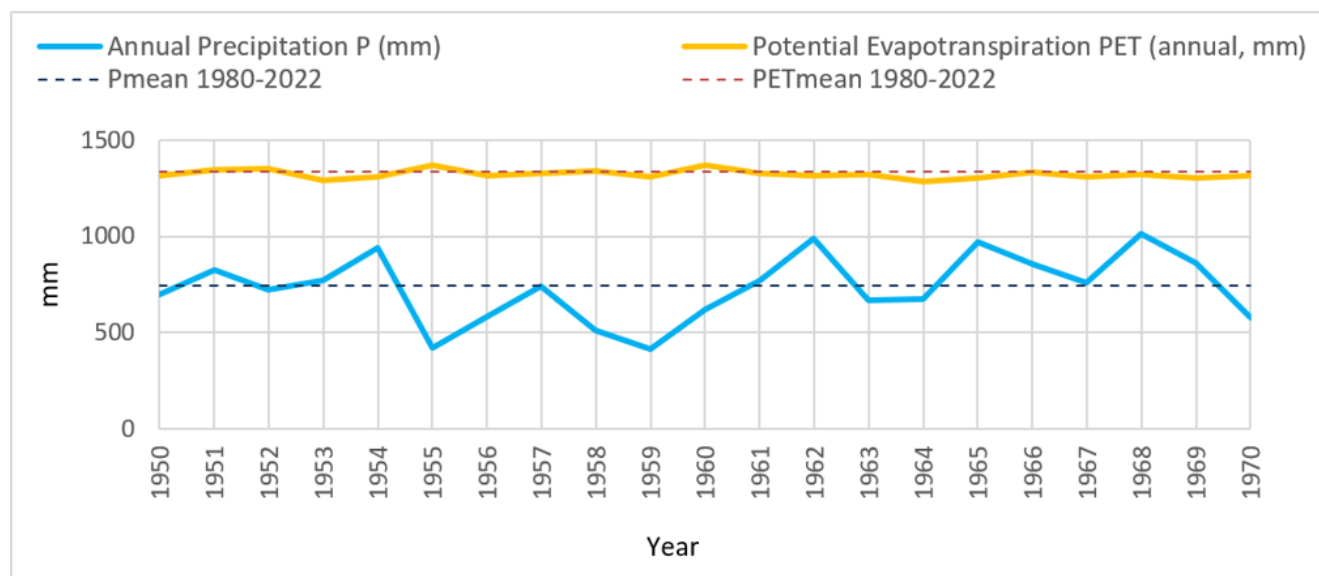


Figure 84: Annual areal precipitation and potential evapotranspiration for the period 1950-1970

Based on the 12-month Standardised Precipitation Index (SPI-12), approximately 71% of all months were classified as near-normal conditions ($-1 \leq \text{SPI} \leq 1$), while 17% of months experienced moderate to extreme drought conditions ($\text{SPI} \leq -1$) indicating that sustained dry conditions constitute a significant component of the basin's hydroclimatic variability. In comparison, 12% of months were classified as moderately to severely wet ($\text{SPI} \geq 1$). These statistics are very similar to those of the 1980-2022 period.

Table 14: Classification of SPI-12 values for the period 1950–1970.

Range of SPI values	Precipitation class	Count (months)	% of months within the period 1980-2022
$\text{SPI} \leq -2.0$	Extremely dry	12	5%
$-2.0 < \text{SPI} \leq -1.5$	Severely dry	10	4%
$-1.5 < \text{SPI} \leq -1.0$	Moderately dry	20	8%
$-1.0 < \text{SPI} \leq 1.0$	Near normal	171	71%
$1.0 < \text{SPI} \leq 1.5$	Moderately wet	23	10%
$1.5 < \text{SPI} \leq 2.0$	Severely wet	4	2%
$2.0 < \text{SPI}$	Extremely wet	0	0%

Based on the SPI-12 analysis, a total of 5 drought events occurred in the Tympaki basin during the period 1950–1970. A drought event was defined as a continuous period with SPI values below zero that reached at least $\text{SPI} = -1.0$ before terminating when SPI became positive again. Drought events ranged in duration from 3 to 39 months and in cumulative magnitude from 4.4 to 56, illustrating the substantial variability in both the persistence and severity of meteorological droughts affecting the basin. The most significant events are summarised in Table 14. The longest and most severe drought occurred between 1957 and 1961, lasting 39

months and reaching a cumulative magnitude of 56. Two additional prolonged droughts occurred during 1955–1957 and in 1963-1964, lasting 28 and 13 months respectively, with cumulative magnitudes of 19.5 and 9, respectively. The two longest droughts (1957-1961 and 1955-1957) account for approximately 78% of the total cumulative drought magnitude recorded during the study period, demonstrating that the hydroclimatic hazard is dominated by the prolonged drought episodes rather than by many short, isolated events, similarly to the 1980-2022 period.

Table 15: Major drought events identified in the Tympaki basin during 1950–1970, showing event duration and cumulative drought magnitude

Years	Duration (months)	Drought magnitude
1957-1961	39	56
1955-1957	28	19.5
1963-1964	13	9
1950-1951	11	8.1
1955	3	4.4

8.6.2. Attribution results

Climate attribution

The first attribution experiment evaluates the influence of climate by comparing simulations forced by the observed ERA5 climate 1951-1970 with simulations forced by the de-trended counterfactual climate generated by the ATTRICI framework, while maintaining the same land use and management conditions throughout the simulation. Table 16 shows that the simulated system performance differs only marginally between the two climate forcings. Mean annual water demand decreases by approximately 1%, while mean annual unmet demand decreases from 5.11 million m³ to 4.98 million m³, corresponding to a reduction of only 2.5%. Similarly, the proportion of unmet demand remains effectively unchanged at approximately 30% of the total demand under both simulations. These mean values of the annual unmet demand are almost identical to one of the contemporary period 1980-2022 (5.23 million m³). These results indicate that, when contemporary land use and water management practices are maintained, replacing the observed climate with the de-trended counterfactual climate produces only minor changes in the simulated performance of the water resources system. This suggests that the long-term evolution of water scarcity in the Tympaki basin cannot be explained by climatic changes alone.

Table 16: Comparison of the water demand and unmet demand statistics with the ERA5 factual climate and the ATTRICI counterfactual climate forcings (1951-1970).

	ERA5 1951-1970					ATTRICI Counterfactual 1951-1970				
	mean	median	Stand. deviation	Max	Min	mean	median	Stand. deviation	Max	Min
Water Demand	17.61	17.26	1.66	20.85 (1952)	15.43 (1963)	17.40	17.10	1.74	20.84 (1952)	15.14 (1963)
Supply Requirement (including loss)	19.46	19.07	1.85	23.06 (1952)	17.04 (1963)	19.23	18.89	1.93	23.05 (1952)	16.72 (1963)
Supply Delivered	14.36	14.46	1.44	17.78 (1952)	11.42 (1960)	14.26	14.46	1.44	17.77 (1952)	11.49 (1960)
Unmet Demand	5.11	4.74	2.12	9.12	2.29	4.98	4.71	2.12	8.88	2.16

	(1960)	(1969)		(1960)	(1969)
Unmet Demand as % of water demand	28%	26%	12%	49%	15%
	(1960)	(1969)		(1960)	(1969)
	28%	25%	10%	48%	14%
	(1960)	(1969)		(1960)	(1969)

Land-use attribution

In contrast, the land-use counterfactual simulations produce substantially larger changes in system behaviour. Restoring land-use conditions representative of the pre-1970 period—before the widespread expansion of irrigated olive cultivation, greenhouse agriculture and public water supply systems—results in a marked reduction in both total water demand and unmet demand (Table 17).

Unlike the climate counterfactual, which alters only the hydroclimatic forcing, the land-use counterfactual fundamentally changes the magnitude and spatial distribution of water demand across the basin (Figure). The resulting reduction in irrigation requirements substantially alleviates pressure on groundwater resources and increases the ability of the system to satisfy water demands. The water supply reliability is very high (95%) for all urban and tourism and agricultural nodes, except for Agri_ 082_Priv which is at 88% (class High).

Table 17: Water demand supply statistics with the ATTRICI counterfactual climate forcing and the Land Use counterfactual (1952-1970).

	Mean	Median	Std. deviation	Max	Min
Water Demand	8.55	7.30	0.91	10.39 (1952)	7.30 (1965)
Supply Requirement (including loss)	9.44	8.05	1.01	11.49 (1952)	8.05 (1965)
Supply Delivered	9.36	5.22	0.96	11.46 (1952)	8.05 (1965)
Unmet Demand	0.08	0.00	0.16	0.65 (1960)	0.00 (1965)
Unmet Demand as % of water demand	1%	0%	2%	7% (1960)	0% (1965)

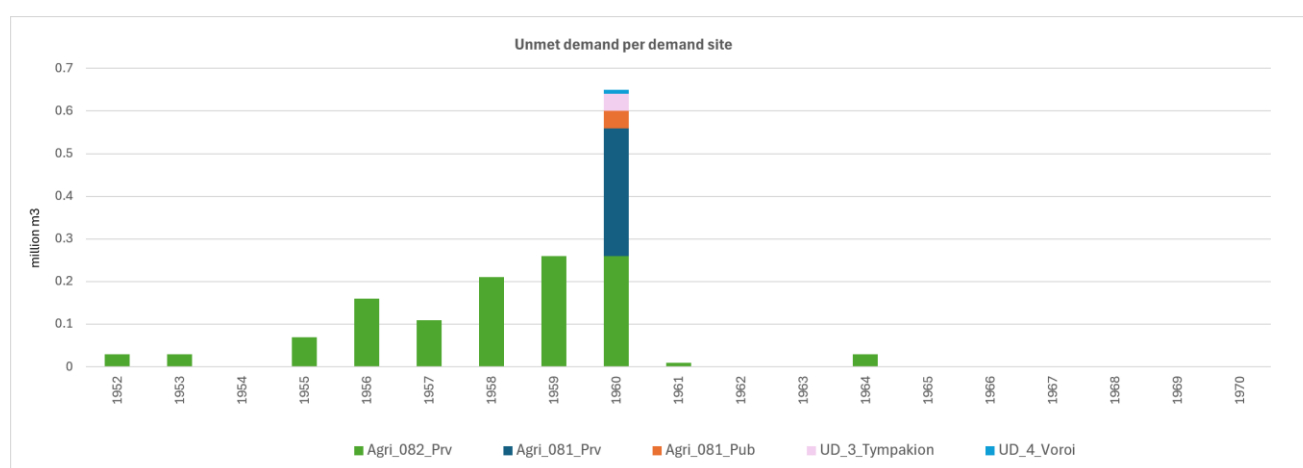


Figure 85: Simulated total annual unmet water demand (1952-1970) per agriculture, urban and tourism demand site under the counterfactual climate and land use scenarios.



Figure 86: Water supply reliability for the agricultural and urban sectors, per demand node (1952-1970), under the counterfactual climate and land use scenarios.

Taken together, these results indicate that changes in land use and the associated expansion of irrigated agriculture constitute the dominant driver of the long-term increase in water scarcity within the Tympaki basin, whereas the climate changes represented by the counterfactual simulations have a comparatively smaller influence on the simulated water deficits.

8.6.3. Stakeholder and policy relevance

The attribution analysis suggests that the evolution of water scarcity in the Tympaki basin is primarily demand-driven rather than supply-driven. Although climatic variability and recurrent droughts act as the triggering hazard, the expansion of irrigated agriculture has substantially increased water demand, amplifying the impacts of drought and leading to persistent unmet water demand. Consequently, land-use change emerges as the dominant factor governing the long-term evolution of water scarcity within the basin over the study period. The quantitative evidence provided can support river basin management planning by identifying whether future reductions in water deficits are more likely to be achieved through demand management measures, land-use planning or climate adaptation strategies. The modelling framework also enables the evaluation of alternative management interventions, including modifications to reservoir operating rules, irrigation efficiency improvements, groundwater abstraction policies and crop pattern changes. Consequently, the framework provides a decision-support tool that can assist water authorities in assessing the effectiveness of adaptation measures before implementation.

More broadly, the methodology is transferable to other Mediterranean basins facing similar pressures from recurrent droughts, intensive irrigated agriculture and competing water demands, demonstrating the potential of integrated attribution modelling to support evidence-based water resources management under a changing climate.

9. Summary and synthesis

This report has detailed the second phase of COMPASS compound event attribution studies, implemented to test, refine, and extend the operational attribution framework and its associated datasets.

A key objective of Phase 2 was to expand the scope and refine the methodologies of the COMPASS framework. While Phase 1 focused on establishing baseline attribution approaches, Phase 2 introduced extensions and innovations to address specific challenges. For example, the USA Tropical Cyclones Use Case employed a probabilistic framework to isolate the role of sea-level rise in damages, while the UK Winter Storms Use Case compared probabilistic and storyline approaches – the latter approach using convection-permitting climate models to better capture temporally compounding and local precipitation extremes. The UK Drought-Heatwave Use Case extended its focus from aviation to rail infrastructure, using DestinE storylines to attribute disruptions to climate change while accounting for infrastructural and socio-economic drivers. The East Africa Tropical Cyclones Use Case revisited TC Idai with ClimateDT storylines, revealing non-linear flood responses to spatial rainfall shifts, while the Honduras Tropical Cyclones Use Case refined its modeling framework (higher-resolution topography, optimized domains) to better represent sequential storm impacts and land-use change. The Durban Flooding Use Case applied SFINCS and Delft-FIAT models to attribute 9–12% of economic damages to climate change, and the Crete Drought Use Case used WEAP21 to assess long-term water scarcity as a systemic, cumulative hazard.

While a key objective of COMPASS remains to develop a uniform modeling framework, Phase 2 intentionally explored diverse configurations, extensions and methodologies to address context-specific challenges. Different attribution methods were implemented, including probabilistic approaches (e.g. USA Tropical Cyclones) and storyline approaches (e.g. UK Winter Storms, UK Drought-Heatwave, TC Idai, Durban). Some use cases, like TC Idai, Honduras TCs, and UK Winter Storms, utilized similar modeling frameworks (SFINCS + wflow), while others, such as USA Tropical Cyclones and UK Drought-Heatwave, employed a new framework (Poisson Pseudo-Maximum Likelihood; DestinE storylines). This diversity facilitated learnings about the advantages and limitations of different approaches across varied contexts. Ultimately, Phase 2 helped advance the science of attribution, demonstrating its potential for policy-relevant insights while also highlighting the need for continued refinement in modeling, data integration, and stakeholder engagement.

Below are summarized the key attributions results for each use case of the Phase 2.

High level summary of attribution results

Use case 1: USA Tropical Cyclones: Anthropogenic sea level rise (SLR) contributed 2.4% (\$4.3 billion) of the total simulated tropical cyclones damages from 1996 to 2024. This signal was statistically robust, driven by well-quantified SLR trends since 1950, and highlighted a clear but modest climate change contribution to coastal flooding impacts. Event-specific variations were notable: storms like Gustav (6.0%), Ida (5.4%), and Rita (5.3%) showed higher SLR-attributable damages, while Katrina (2.1%) had a lower contribution, likely due to model limitations in representing storm surge and levees. Under a +1m SLR scenario, damages were projected to increase by 10.6% (\$18.7 billion), underscoring the non-linear escalation of coastal flood risks as SLR accelerates.

Use case 2a: UK winter storms 2013/14 – Extended: Both the probabilistic (Phase 1) and storyline (using convection-permitting climate model data) approaches detected a small but consistent increase in flood extent due to climate change (considering areas with flood depth greater than 0.3 m). The storyline approach yielded a slightly stronger climate signal (e.g., 0.9% increase in flood extent since 1990 vs. 0.55% since pre-industrial in Phase 1) but with large uncertainties in the probabilistic approach. Phase 2 also extended the analysis to a +3°C world, showing slightly higher flood impacts between the future and factual scenario (+1.3% for flood extent; +2.8% for flood volume) compared to the factual and counterfactual (+0.9% for flood extent; +2.2% for flood volume) due to increased precipitation intensity. Consecutive storms were found to compound flooding more

severely than isolated events. While maximum flood extent, depth and volume showed little differences across the different climates, the onset of flooding was significantly faster in the factual and future scenarios compared to the counterfactual. This highlights the importance of temporal metrics (e.g. rate of precipitation) alongside traditional metrics (e.g. precipitation accumulation).

Use case 2b: UK Drought-Heatwave 2022 – Extended: In Phase 2, the UK drought-heatwave's impact on the rail network (infrastructure, cancellations) was mostly attributed to post-1950 climate change. High-impact temperature thresholds linked to train cancellations (48-50 °C rail temperatures) were not exceeded in the 5-member ensemble counterfactual simulations (using delta-adjusted DestinE storylines). However, lower thresholds (e.g. 47°C) likely causing disruptions were still exceeded, suggesting disruptions would have occurred even without climate change: cancellation rate would have decreased from 75% to 30-35% for the East Coast Main line, and from 55% to 15-20% for the London North Western South. The hottest day (19 July) did not coincide with the worst impacts (18 July), due to cloud cover differences. This highlights that heatwave impacts are multivariate, depending on other factors than just air temperature (e.g. soil moisture, cloud cover).

Use case 3: TC Idai, East Africa 2019 – Extended: Both approaches (Clausius-Clapeyron in Phase 1; ClimateDT storylines in Phase 2) showed increased flood impacts related to climate change. For TC Idai, the analysis revealed that climate change increased flood extent by 5% and flood volume by 11%, compared to 2% and 9% in Phase 1; even with a smaller counterfactual area-aggregated rainfall decrease (4% vs 8% in Phase 1). This might be explained by the strong influence of spatial variability present in the ClimateDT storylines. Along with temporal variability and the uncertainty emerging from meteorological parameters, it provides insight on the non-linear responses in river discharge and flood modelling.

Use case 4: Iota & Eta, Honduras 2020 – Extended: Unlike Phase 1, which found no clear change in flood extent or exposure, Phase 2's refined modeling framework revealed a small but detectable climate signal, with higher precipitation intensity in the factual scenario leading to increased river discharges (most notably for Rio Ulua and Rio Chamelecon) and larger maximum flood depths across the Sula Valley, resulting in 2.9% and 3.5% increase in people and building exposure, respectively. The study also explored a non-climate counterfactual (deforestation), using two versions of land cover datasets (100m and 10m resolution). Both datasets showed that deforestation reduced surface roughness, causing water to flow faster downstream and resulting in lower maximum flood depths in the deforested (factual) scenario. However, the magnitude of this effect varied between datasets, with the 100m dataset showing a larger difference in flood depth due to its assignment of more cropland to the counterfactual, while the 10m dataset shows a smaller, more localized difference driven primarily by roughness changes. This highlights the uncertainty in global land cover products and the limitations of current models, which represent land-use change only through surface roughness, neglecting other processes like infiltration, interception, evapotranspiration, or erosion.

Use case 5: Durban Flooding: For attribution, the study employed two counterfactual approaches:

1. Clausius-Clapeyron scaling: Precipitation reduced by 8% to simulate a pre-industrial climate, attributing 9.45% of flood volume (+13.88 Mm³), 3.86% of flood extent (+3.91 km²), and 5.82% of mean depth (+0.09m) to climate change.
2. ClimateDT storylines: Compares present-day vs. pre-industrial climates, attributing 11.82% of flood volume (+17.36 Mm³), 4.85% of flood extent (+4.92 km²), and 7.32% of mean depth (+0.11m) to climate change.

Both methods converged on a comparable climate signal, attributing 9–12% of economic damages (\$79.3–99 million) and 3–4% of exposed population (686–846 people) to anthropogenic warming. The climate signal was strongest in high-damage areas (e.g., Harbour and Southwest Durban), emphasizing the non-linear amplification of impacts in vulnerable hotspots.

Use case 6: Crete Drought: The attribution analysis shows that the long-term deterioration of water resources in the Tympaki basin cannot be explained by climatic changes alone. Simulations comparing the observed climate with a counterfactual climate representative of pre-1980 conditions (i.e. 1950-1970) indicate only marginal differences in water demand, water supply and unmet demand when contemporary land use and water management are retained. In contrast, simulations representing historical land-use conditions (1950-1970) produce substantially lower water demands and markedly reduced water deficits. The mean annual unmet demand in that case is approximately 0.08 million m³ compared to the 5.23 million m³ of the 1980-2022 period with the current land use conditions. This clearly demonstrates that the expansion of irrigated agriculture, increased groundwater abstraction, and associated water management changes have been the dominant drivers of increasing water scarcity. The results therefore indicate that recurrent hydroclimatic droughts provide the natural hazard, but the severity of water scarcity is primarily determined by the evolution of human water demand and land-use practices. Consequently, effective adaptation should focus not only on improving resilience to climate variability but most importantly on sustainable water allocation, demand management, efficient irrigation practices and integrated land and water resources planning.

Key lessons learned

Use case 1: USA Tropical Cyclones: Key lessons learned include the importance of SLR as a detectable climate signal in tropical cyclone damages, despite its relatively modest contribution compared to the total economic losses. The event-specific nuances highlighted the importance of storm surge dynamics and the need to account for structural failures (e.g., levees) in modeling, as these can significantly influence attribution results. The study also revealed data limitations, such as incomplete damage records in the NCEI Storm Events Database and challenges in validating modeled damages against observed impacts. Additionally, the compounding effects of non-climate drivers, such as coastal development and exposure growth, likely influence the climate signal, emphasizing the need to disaggregate climate and non-climate contributions in future analyses. Methodologically, the use of counterfactual baselines (e.g. no-SLR vs. +1m SLR) provided actionable insights for risk assessment and adaptation planning, but future work should explore higher-resolution models to capture local surge dynamics more accurately. For stakeholders, the results underscore the importance of framing SLR as a growing risk multiplier, which can inform coastal protection investments, insurance reforms, and risk-informed land-use policies to mitigate future damages.

Use case 2a: UK winter storms 2013/14 – Extended: Key lessons learned from the UK Winter Storms Use Case include the importance of metric choice: standard metrics like maximum flood extent may mask critical differences in temporal dynamics, which are vital for emergency response planning. The storyline approach (using a 1990s baseline) produced a stronger climate signal than the probabilistic approach (pre-industrial baseline), aligning with broader findings in rainfall attribution studies that recent baselines may better capture observed trends in precipitation extremes. Additionally, the study underscored the critical role of high-resolution data: the use of a global DEM (FABDEM, 30m) in Phase 2 performed less well in validation compared to the local, higher-resolution DEM (LiDAR-based) used in Phase 1, highlighting the need for local data to improve model accuracy, particularly in complex urban or topographic settings like Bridgwater. The use of convection-permitting rainfall data (UKCP Local at 2.2km) also revealed stronger climate signals than the coarser global model (HadGEM3-A at 60km), reinforcing the importance of high-resolution inputs for capturing local extremes and translating them into impact-relevant signals.

Use case 2b: UK Drought-Heatwave 2022 – Extended: Key lessons learned from the UK Drought-Heatwave Use Case include the effectiveness and limitations of DestinE storylines: while they reproduce the broad spatial extent of heatwave events across climates, they suffer from large biases (e.g., a ~4.5°C cold bias in maximum temperatures for the 2022 heatwave), which prevent direct use for impact modeling. Instead, delta adjustments

(applying the difference between factual and counterfactual storylines to observed data) emerged as a practical workaround, a theme also observed in other COMPASS use cases. The study also highlighted the challenges of modeling indirect climate impacts: while the analysis captured some multivariate aspects (e.g., air temperature + shortwave radiation), drought-induced ground movement (leading to track deformation) remained difficult to model with the current configuration, pointing to a gap in representing cascading or indirect risks. Additionally, the temporal and spatial scale mismatches in impact data (e.g., rail disruptions) made it difficult to assign weather events as direct causes, emphasizing the need for higher-resolution, causal impact datasets. Finally, the study underscored the amplifying role of exposure: increased rail usage since 1980 significantly amplified the number of passengers exposed to disruptions, with projected growth (e.g., +37–97% by 2050) set to further exacerbate impacts. This reinforces the need to integrate exposure trends into attribution frameworks to fully capture the drivers of risk.

Use case 3: TC Idai, East Africa 2019 – Extended: The construction of plausible climate storylines is not straightforward, and results are sensitive to methodological choices. The high-resolution ClimateDT storylines provide a physically consistent way to construct storylines for tropical cyclones, representing an improvement from the Clausius-Clapeyron (CC) approach used in Phase 1. From a meteorological perspective, the ClimateDT storylines appear relatively robust, and total changes in flood hazard are of the same order of magnitude between methods (9% and 11% increase in flood volume for CC and ClimateDT, respectively). However, when translated into flood impacts, the hydrological system's non-linear response and changes in the spatial structure of the event strongly influence estimated impacts, and it remains unclear whether such changes can be directly linked to climate change. ClimateDT storyline simulations are therefore a useful basis for climate attribution, but developing methods to distinguish and quantify the climate change signal from model uncertainty (particularly for changes in the spatial patterns of precipitation) remains important. Access to multiple realizations of the storylines (ClimateDT generation 2 data, recently made available) helps but does not entirely remove model uncertainty. Building further experience in interpreting climate storylines together with the meteorology and flood hazard modelling communities, through additional use cases, will be needed to advance this method.

Use case 4: Iota & Eta, Honduras 2020 – Extended: The Phase 1 use case was extended to improve the accuracy of the flood modelling framework. Validation against satellite-derived flood maps showed reasonably good performance, greatly increasing confidence in the attribution results compared to Phase 1. The improvements were mainly driven by the use of a better digital elevation model (DEM), consistent with many studies pointing to the DEM as one of the most critical elements in defining the pathways through which water can flow. Features such as bridges, culverts, and other obstructions are often poorly resolved, and can significantly affect flow pathways. This highlights the importance of validation data where possible, and of incorporating local knowledge to better understand the uncertainty of flood hazard modelling. It was also clear that land use changes (e.g. deforestation) can yield very different results, but it remains difficult to model all the processes through which deforestation influences flood magnitude: not just surface roughness, but also soil infiltration and evapotranspiration. Further development of the modelling framework, building on wflow and SFINCS, would be needed to capture these processes; this is a clear research gap and a relevant avenue for future work. More generally, the threshold used to classify a location as flooded was found to influence results, and attribution studies should clearly document this methodological choice.

Use case 5: Durban Flooding: The comparison of two attribution methods (CC scaling vs. ClimateDT) showed no major differences, with climate attribution of flood hazard and impact comparable and of the same order of magnitude (9–12% for damages), a conclusion broadly consistent with that reached for TC Idai. ClimateDT yielded slightly higher estimates than CC scaling, likely reflecting spatial variability in precipitation that the uniform 8% CC-scaling reduction could not capture. Despite offering higher resolution than other spectrally nudged storyline datasets, ClimateDT still showed, for the Durban event, differences between scenarios that could not be exclusively attributed to thermodynamic climate change, a limitation also documented in other

spectrally nudged datasets. Notably, similar limitations emerged for TC Idai, a markedly different event type (tropical cyclone vs. subtropical depression), suggesting these are not case-specific artefacts. This indicates that while nudged storyline data and methods are intended to isolate thermodynamic differences between climate states, they show limitations when applied to flood events. For Durban specifically, larger ensembles and higher spatial resolution (~3 km) could help resolve the convective elements underlying the event. In this case, attribution is largely dependent on how the event itself is defined, with different definitions leading to different attribution statements. Developing a protocol for defining flood events within an attribution context is recommended.

Use case 6: Crete Drought: Key lessons learned from this use case include the value of adopting a system attribution approach for water scarcity, recognising that impacts arise from the interaction of climatic, hydrological and socio-economic processes over multiple decades rather than from a single extreme event. The analysis demonstrates that water scarcity in the Tympaki basin cannot be attributed to climate change alone, but instead results from the combined effects of recurrent droughts, land-use change and increasing water demand. The WEAP-based modelling framework proved effective for evaluating alternative historical scenarios and quantifying the relative influence of different drivers on basin-scale water resources. The analysis highlights that long-term drought impacts depend not only on climate variability but also on exposure and water demand created through land-use change and agricultural development. In Mediterranean basins such as Tympaki, sustained irrigation expansion can outweigh the effects of climatic changes on overall water scarcity. The study also illustrates that attribution based solely on climate signals may underestimate the importance of socio-economic drivers and water management decisions. Counterfactual simulations provide a robust means of separating these interacting influences and supporting evidence-based adaptation planning. The findings emphasise the importance of integrating climate information with land-use planning, groundwater management and demand-side measures when developing adaptation strategies. Finally, the methodology developed here is transferable to other water-stressed basins where long-term changes in climate, land use and water management interact to shape water security, providing a practical framework for supporting integrated water resources management and climate adaptation decisions.

Stakeholder and Policy Relevance

As in Phase 1, several UCs in Phase 2 highlighted concrete implications for stakeholders and policy. The USA Tropical Cyclones UC underscored the value of framing sea level rise as a growing risk multiplier, results that can inform coastal protection investment, insurance reform, and risk-informed land-use policy along the Atlantic and Gulf Coasts. UC2a (UK winter storms) demonstrated the practical importance of temporal metrics (not just maximum flood extent) for emergency response planning, given that the onset of flooding was found to be significantly faster under factual and future climate scenarios. UC2b (UK drought-heatwave, extended to rail) pointed to the need for infrastructure resilience planning for the rail network, with projected passenger growth (+37–97% by 2050) set to amplify future disruption, reinforcing the relevance of the attribution results to long-term adaptation planning for transport infrastructure. For UC3 (TC Idai) and UC4 (Honduras), results continued to support the case, first raised in Phase 1, for greater investment in early warning systems and resilient infrastructure in vulnerable regions, while the improved modelling framework in Honduras strengthens confidence in these results for decision-making. UC5 (Durban) highlighted a more methodological policy relevance: because attribution outcomes were found to depend strongly on how a flood event is defined, the UC recommends developing a standardised protocol for event definition to ensure attribution studies produce defensible statements for policymakers. UC6 (Crete) offered the clearest policy message of Phase 2, showing that water scarcity in the Tympaki basin is driven primarily by irrigation expansion and water management rather than climate alone, directing adaptation efforts toward sustainable water allocation, demand management, and

integrated land and water resources planning, with a methodology that could be transferable to other water-stressed Mediterranean basins.

Compared to Phase 1, where stakeholder relevance centred on how attribution results could justify specific infrastructure and early-warning investments, Phase 2's policy messages are more methodological, emphasising how attribution should be done (event definition protocols, high-resolution and validated data, multi-method uncertainty quantification) alongside what it recommends. The Phase 1 finding that impacts in Mozambique and Honduras were amplified by socio-economic processes (e.g. poverty, weak infrastructure, political fragility) is reaffirmed and extended in Phase 2, most notably through the Crete UC, which demonstrates that non-climate drivers can, in some contexts, outweigh the climate signal entirely. This continuity across phases strengthens the case, first made in Phase 1, for socially inclusive resilience and adaptation planning that treats climate attribution as one input among several needed to design effective, locally grounded policy responses.

Conclusion

The results confirm that climate change is a detectable, and in several cases strengthening, contributor to the impacts of extreme events, from sea-level-rise-driven tropical cyclone damages in the United States to compound flooding in East Africa, Honduras, and Durban. At the same time, Phase 2 reinforces a central message from Phase 1: climate signals rarely act alone. Exposure growth, land-use change, infrastructure vulnerability, and water management decisions were repeatedly shown to shape, and sometimes outweigh, the direct influence of a changing climate on observed impacts. The Crete drought case illustrates that some hazards are best understood not as discrete extreme events but as slow-onset, cumulative outcomes of interacting climatic and socio-economic processes over multiple decades.

Methodologically, Phase 2 demonstrates that the COMPASS framework is flexible enough to use diverse attribution methods and data sources while still enabling meaningful cross-case comparison. The introduction of ClimateDT and DestinE storyline datasets alongside more established approaches (Clausius-Clapeyron scaling, probabilistic risk-based methods) has provided valuable insight into both the added value of physically consistent, high-resolution storylines and their limitation, particularly in isolating thermodynamic climate signals from spatial variability and model uncertainty. These limitations were not confined to a single event type or region, suggesting they reflect methodological gaps rather than case-specific artefacts.

Looking ahead, several priorities emerge for the continued development of operational climate attribution within COMPASS and beyond: further investment in high-resolution, locally validated data, particularly in data-scarce regions; the development of standardised protocols for defining events and impact thresholds, to ensure attribution results are comparable and reproducible; deeper integration of cascading, indirect, and socio-economic drivers of impact into quantitative modelling frameworks; and continued multi-method validation to robustly characterise uncertainty. Sustained engagement with the meteorological, hydrological, and stakeholder communities will remain essential to translating these advances into attribution science that is not only methodologically sound, but genuinely useful for adaptation planning and policy decisions in a changing climate.

10. Annexes

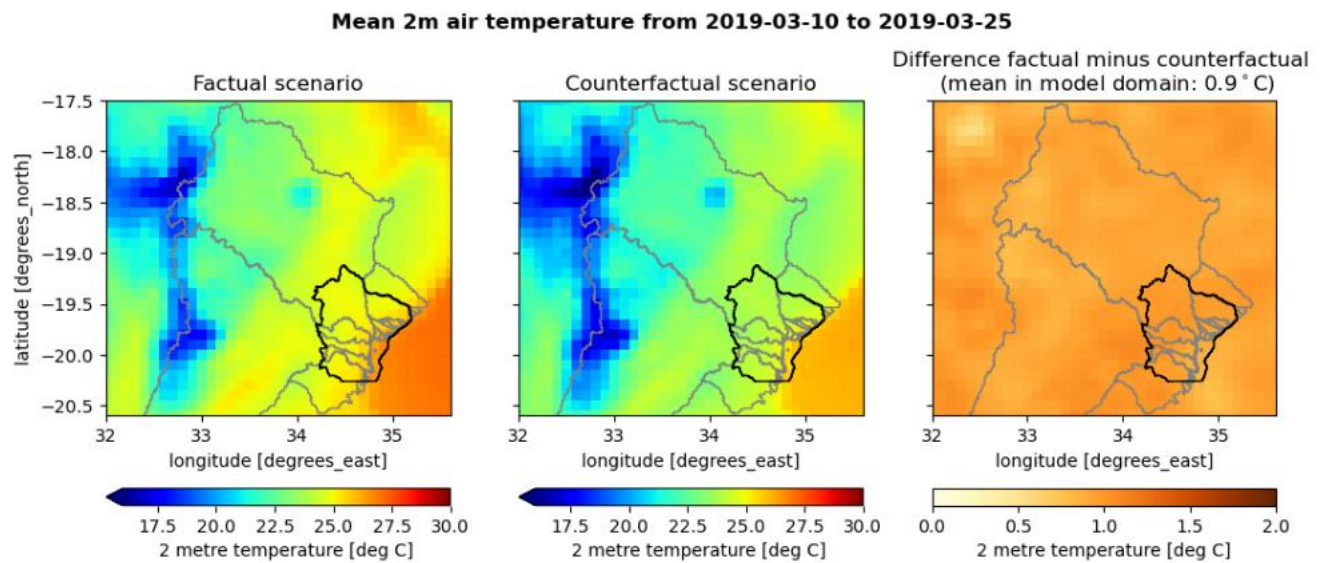


Figure 45: Mean temperature difference between factual and counterfactual scenarios from ClimateDT storylines of approximately 0.9 degrees is consistent with global warming estimates between 1950 and 2019.