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COMPASS

Report documenting the developments in conditional attribution and results from initial application

Deliverable 2.5

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Executive summary

Deliverable 2.5 'Report documenting the developments in conditional attribution and results from initial application' summarizes the key lessons learnt in conditional attribution from the first two years of the COMPASS project (2024-2026). It draws on developments from deliverables in this work package, WP2 "Attribution frameworks in a physical context", around large-scale drivers and complex extremes from D2.2 and D2.3 (Rushby et al., 2025; Rushby 2025), as well as the lessons learnt from the COMPASS attribution Use Cases in WP4 " Developing actionable climate information for events"; from deliverable *D4.1 'Hazard and Impact Synthesis and Attribution for Phase I use case'* (Jack et al., 2025). This deliverable will feed into and is closely linked to *D2.7: Report on recommendations for attribution methods suitable for compound events with damaging impacts* (Cotterill et al., 2026).

One of the main goals of the COMPASS project is to extend attribution methodologies for single-driver extremes to multi-driver (complex) extremes, aiding development of a harmonized methodological framework for climate impact attribution for complex extremes. There are a wide range of attribution methodologies for single-drivers ranging from highly conditioned approaches (storylines) to more unconditional approaches (risk-based). Different attribution approaches answer different questions, such as how climate change is influencing the duration, intensity or likelihood of the event, or simply understanding the key drivers of the event (Thompson et al., 2025). It has already been shown that the choice of conditioning for the same event can lead to different results in attribution studies, even when using the same model data (Buschow et al., 2024; Leach et al., 2024).

Based on the first set of COMPASS use cases, this report finds that the application of attribution methods to more complex extremes and specifically impact attribution requires extra choices around conditioning since that can have a significant impact on the results. Therefore, it is important for impact attribution that stakeholder engagement and a clear focus on which science question(s) the study aims to answer is addressed at an early stage, to provide the most useful output. The report also highlights that the choice of impact attribution methods and hence conditionality is still very limited for certain complex extremes such as Tropical Cyclones (TC), where very strong conditioning is required to combat the extra uncertainty introduced in the attribution results from the impacts side. Furthermore, this report documents a framework developed in the COMPASS project in WP2 linking large-scale drivers to complex extremes and its application to one of the Use Cases. This framework has strong potential to guide the choice of conditionality for impact attribution studies looking at complex extremes and adding valuable input to attribution studies.

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Glossary

Anthropogenic Climate Change: Long-term increase in mean global temperatures resulting from human activity

Climate Change: Long-term increase in mean global temperatures driven by human activity including natural factors

Climate Counterfactual: What the climate would have looked like without some or all human influence on the climate. Could be representative of a pre-industrial climate or a climate in the past (i.e. 1950 baseline).

Temporally compounding: A succession of hazard events leading to amplified impacts

Spatially compounding event: Co-occurrent hazard events at different locations, the combination of which leading to amplified impacts

Preconditioned event: Pre-existing climate condition in combination with a hazard leading to an amplification of the impacts of the hazard

Multivariate nature: Multiple hazards or meteorological extremes at the same location leading to amplified impacts

ERA5: Reanalysis v5 produced by the European Centre for Medium-Range Weather Forecasts (ECMWF) (Hersbach et al., 2020)

Exposure: Population or assets exposed to an extreme event

Vulnerability: Susceptibility of people/assets exposed due to socio-economic and environmental factors

SST: Sea Surface Temperatures

WP: Weather Patterns

Large-scale drivers: Predictable features of the global weather and climate system, that impact regional and global weather in different ways

1. Introduction

Climate event attribution methods are often categorized as probabilistic or risk-based (i.e. looking at a class of events, hence tend to be more unconditional in nature) or storylines (i.e. a specific event very highly conditioned) (Shepherd, 2018). However, it is important to note that there is a spectrum, with different attribution methods varying in their level of conditioning, and all answering different questions (Thompson et al., 2025). A lot of research and analysis has been carried out, discussing the benefits of both more risk-based and storyline methods (e.g. Jézéquel et al 2018; Shepherd, 2016; Coumou et al., 2024; van Garderen and León-FonFay, 2026), with general agreement that both can provide useful strands of information and that it is best to use a wide range of methods, if possible, to assess confidence in the results and understand how the results relate to each other.

The main goal of the COMPASS project is to develop a harmonized yet flexible methodological framework for climate, impact and event attribution of complex extremes covering but not limited to multivariate, compounding, and pre-conditioned hazard events. The Phase 1 Use Cases in D4.1: 'Hazard and Impact Synthesis and Attribution for Phase I use case', is a testbed to address this through case studies for a range of events and regions (Table 1). These case studies also implemented a range of methods with varying conditionality. The use case leads from all six studies filled in a survey and were interviewed on their chosen attribution methodology and the lessons learnt. A summary of this content in relation to conditional attribution for their studies will be discussed in this report.

Table 1 Complex events examined in COMPASS used for Phase 1 impact attribution studies (Source: Jack et al., 2025).

Name and date	Geography	Hazards	Compounding	Attribution method	Lead institution
UC1 – Xynthia 2010	France – west coast and inland	Wind, storm surge – coastal flooding	Multivariate/spatially	Storyline	PIK
UC2a – United Kingdom winter storms (2013/2014)	United Kingdom, Somerset	Rainfall, wind, storm surge, flooding (fluvial, pluvial, coastal)	Multivariate, temporal	Probabilistic	Met Office
UC2b – United Kingdom drought heatwave (2022))	United Kingdom	Drought, Heat wave	Multivariate, spatial	Probabilistic	Met Office
UC3a – East Africa Cyclones Idai and Kenneth (2019)	East Africa, Mozambique	Wind, storm surge, rainfall, flooding (fluvial, pluvial, coastal)	Multivariate, spatial	Storyline	Deltares
UC3b – East Africa Cyclone Freddy (2023)	East Africa	Wind, storm surge, rainfall, flooding (fluvial, pluvial, coastal)	Multivariate, spatial	Storyline	Deltares
UC4 – Tropical storms Eta and Iota (2020)	Caribbean, Honduras	Rainfall, flooding (fluvial, pluvial), COVID-19, Violence	Multivariate (non-climate) Temporal	Storyline (quantitative and qualitative)	Red Cross Red Crescent Climate Centre

The first section examines the additional choices in the level of conditioning required when studies are extended to include impact attribution. Section 3 focusses on the lessons learnt from the COMPASS phase 1 use cases with a detailed examination of the conditionality used within each case. Section 4 draws upon common themes across the use cases in relation to impact attribution approaches of different conditioning for complex extremes. Understanding the key large-scale drivers of complex extremes can inform the choice of attribution method and hence conditionality. In WP2, a framework is developed in Deliverable 2.2 to link large-scale drivers to complex extremes, such as compound events. In the final part of this report (Section 5), we provide an overview of this framework, its application to UC2a, and how it could inform conditional attribution.

2. Breaking down conditionality in impact attribution

The discussion of risk-based vs storyline attribution methods has focused predominantly on conditionality from a hazard attribution perspective, where event attribution is carried out for single location value (average value over a chosen domain) and metric (e.g. daily-max temperature or 5-day maximum rainfall). However, as demonstrated by the results of the Use Cases in the COMPASS project, there are extra strands of conditionality introduced when extending to impact event attribution (particularly for more complex extremes), not captured by the traditional attribution definition of conditional attribution.

In this section, we explore these extra strands through the wide range of impact attribution methodologies applied in Phase 1 COMPASS Use Cases. For impact attribution, we dissect the conditionality into three categories; the first category encompasses conditionality in the traditional hazard attribution sense, along with two new categories (Spatial-temporal and Impact-modelling) that are introduced when applying impact event attribution. The definition for each category of conditionality is given below:

- **Hazard Attribution (Synoptic)**: Classic definition of conditionality in hazard attribution. Spectrum ranges from unconditional on synoptic conditions (i.e. class of events) to highly conditioned (i.e. Pseudo Global Warming (PGW) experiments)
- **Spatial temporal (Event structure)**: To go from hazard event attribution to impact event attribution, an additional choice (the spatial-temporal conditioning) is required. Temporal duration and spatial extent are important for Impact Attribution. Unconditional (i.e. counterfactual is represented by wide range of spatial-temporal event structures) to highly conditioned (i.e. counterfactual has the same spatial-temporal structure as the observed event structure). In the case of the highly conditioned counterfactual, a common method would be to apply a percentage change in intensity to the observed hazard data to produce the counterfactual (hence keeping the spatial-temporal structure of the event the same).
- **Impact modelling (Boundary conditions):** Unconditional (i.e. testing range of boundary conditions) to highly conditioned (i.e. based on a single set of boundary conditions). Examples of boundary conditions include initial river flows and low/high tides.

Communicating and understanding the different choices in conditionality for each category is important, as different choices will answer different attribution questions and provide different information. Thompson et al., 2025 describes four different characteristics of events that attribution can answer; the change in frequency, intensity change, change in duration, and drivers of the change (could include local processes or long-term forcings). Therefore, engagement with relevant stakeholders over which questions they are most interested in has the potential to shape the conditionality of choices in a way that the attribution output is most useful. Firstly, however, a broader understanding of what choices are viable given the current state of impact attribution is needed. The learnings from the choice of conditionality in each of three categories are discussed in the next section for the Phase 1 Use Cases. For each use case we assess the level of conditionality for each of the three conditionality categories that we have defined in this section (i.e. hazard, spatial temporal, and impact).

3. Conditional Attribution Learnings: Use Cases Phase 1

There were six use cases in the Phase 1 part of the COMPASS project. The event summary, attribution methodology overview and results summary for each one are described below based on material from D4.1 'Hazard and Impact Synthesis and Attribution for Phase I use case' (Jack et al., 2025). The level of conditioning in each of the three categories defined above is then explored in more detail for each use case.

3.1. Use Case 1: Storm Xynthia 2010 in France

Event:

Storm Xynthia on the 28th February 2010 brought compounding impacts to France through both widespread windstorm damage and coastal flooding. Impacts included over 2.5 billion euros in damages and 47 fatalities. In the attribution study, the impacts from climate change on both the windstorm aspect and coastal flooding are analysed individually. The event was both multivariate and spatially compounding.

Attribution Methodology Overview:

For the coastal flooding component, a storm surge model (Delft3D) is used with the main inputs being sea level, and storm surge heights. The method to produce counterfactual storm surge heights is tsEVA (Mentaschi et al., 2016), a transformed-stationary extreme value analysis methodology that that can calculate the return period of the event in both the current climate and 1950 baseline using ERA5 data. The sea level rise counterfactual uses data from 1950-2020, to subtract the sea level rise since 1950 based on long-term trends.

The attribution of the windstorm component used two different methods. Method 1 (M1) used the tsEVA approach based on ERA5 data since 1950, and Method 2 (M2) used event period (2006-2013) and preindustrial climate model simulations from the HadGEM3-A model. These runs are conditioned on observed sea surface temperatures, with the counterfactual ensemble members having the anthropogenic influence on SST and sea ice components removed (Ciavarella et al., 2018). The first attribution method uses trends since 1950, whereas the second method measures the anthropogenic climate change component through a preindustrial baseline, therefore answering slightly different questions.

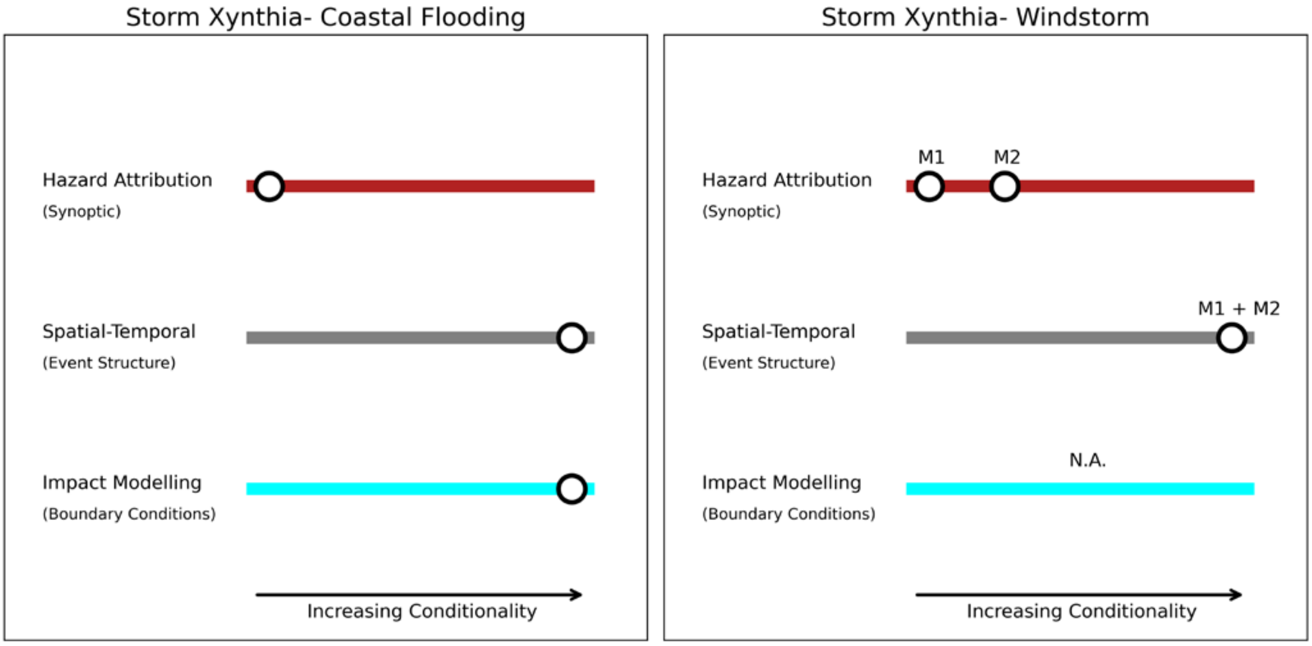

Figure 1 Compound conditionality impact attribution diagram for the Storm Xynthia Use Case.

Results:

Climate change has increased the impacts of coastal flooding for the event by 10-14%, predominantly due to sea level rise since 1950. Both attribution approaches for windstorm damage show an increase in economic damage by 22% (CI not quantified) in Method 1 and 7% (90CI: -71 to +44) in Method 2 in a factual climate compared to a 1950- baseline/preindustrial climate respectively. Therefore, the analysis concluded that there is strong confidence that coastal flooding impacts have increased due to climate change, with some indication (given that both methods show a similar result) that windstorm damage has increased due to climate change. However, for the wind storm the 90% uncertainty intervals are very large and include both negative and positive change. Therefore, there is less confidence in the results.

What are the conditional choices?

For the hazard attribution of coastal flooding components (Figure 1), both storm surge height and long-term sea level rise are based on long term trends using data from multiple years. Therefore, from a hazard attribution perspective this is an **unconditional** approach as wind speeds and the sea level pressure data that go into the storm surge model are based on multiple events and synoptic setups. However, when applying impact modeling, the spatial-temporal structure is **conditional** on the structure of the 2010 event. Furthermore, the boundary conditions in the model include tides which are **conditioned** on the high tides seen during the event. Coastal flooding impacts are likely to be very sensitive to both tide levels and the spatial-temporal structure. Therefore, keeping them conditioned can reduce uncertainty in the overall hazard attribution results, with an impact attribution statement very specific to this storyline (i.e. high tides and specific storm path) and hence be more useful for risk-managers interested in the specific event.

For the hazard attribution of the windstorm components, two attribution methods were used (Figure: 1). Both the detrending approach using tsEVA (M1) and climate ensembles approach (M2) are **unconditional** in terms of the hazard. The ensemble approach is slightly more conditioned as it only uses climate simulations conditioned on 2006-2013 Sea Surface Temperature patterns, where the level of conditioning is very dependent on the influence of the ocean state on the event in question (i.e. if the SST patterns are a key driver of the event, this approach would be more conditioned than if it wasn't a driver). The main differences included the baseline (1850 for M2 and 1950 for M1), the data used to calculate the counterfactual (ERA5 reanalysis for M1, and preindustrial and current climate model runs for M2) and the method applied. In M2, the method is based on changes in SSTs and sea ice content due to anthropogenic climate change, whereas in M1 a non-stationary extreme value analysis detrending method is used since 1950.

The two methods are applied to a damage function relating wind speeds to economic losses. The factual wind speed was the observed event. The counterfactual climate used either the detrending method (M1) or the difference between the preindustrial climate runs and present climate (M2), to perturb the wind values of the observed event to represent the counterfactual climate. The wind perturbations for the counterfactual were calculated for each grid box individually, therefore keeping the same temporal-spatial structure to the wind event as seen on the 28th of February 2010 (**highly-conditioned**). The third category of conditionality did not apply to this case as there were no specific boundary conditions, such as those for more hydrological-based impacts.

3.2. Use Case 2a: UK 2013-14 winter storms

Event:

In the winter of 2013/14 a succession of at least 12 storms within a 3-month period (Kendon and McCarthy, 2015) brought flooding of multiple types (pluvial, fluvial and coastal) to the UK. The economic cost of this succession of storms reached £1.3 billion for England and Wales. The focus of this use case was the flooding of the Somerset Levels in south-west England, which corresponded to 30% of the flooded agricultural land in the

UK over this period. This event was both temporally (successive storms) and multivariate compounding (sea-level rise and extreme rainfall, as well as multiple types of flooding).

Attribution Methodology Overview:

To simulate flooding from multiple rainfall events, climate model simulations (HadGEM3-A runs) of winter rainfall in both a factual (2005-2024) and counterfactual (pre-industrial) climate were used. These runs are conditioned on observed sea surface temperatures from 2005-2024, with the counterfactual ensemble members having the anthropogenic influence on SST and sea ice components removed (Ciavarella et al., 2018). This factual and counterfactual data was inputted into the Deltares flood modelling framework (Deltares, 2026), which contains a hydrological model for river flows and a hydrodynamic model to represent compound flooding. The initial river flows at the start of each winter are calculated using a warmup period for the hydrological model of a year before the start of the hydrodynamic simulation. The warmup period is run with ERA5 data.

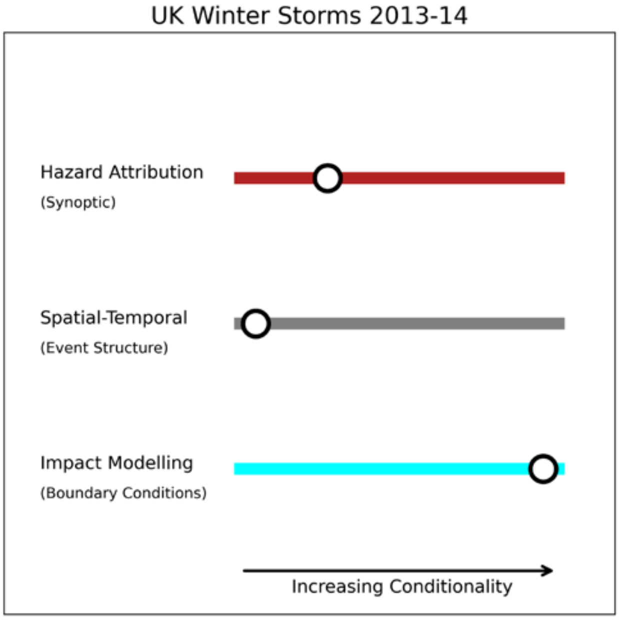

Figure 2 Compound conditionality impact attribution diagram for the UK winter Storms Use Case.

Results:

Anthropogenic climate change is found to have slightly increased the magnitude of the flood extent over the Somerset Levels, with the likelihood of exceeding that flood extent 1.2 times more likely in 2013/14 than in a pre-industrial climate. However, there is little confidence in the results given the large uncertainties in the 95% confidence intervals (between 3 times less likely and 4.5 times more likely).

What are the conditional choices?

The hazard data for the attribution contains multiple winters, with different numbers of storms and synoptic set ups, and therefore is a more **unconditional** approach (Figure 2). However, there is a small amount of conditioning in this approach given that the SST patterns are fixed on those between 2005-2024 in the runs. When applying the impact attribution, we simulate multiple winter rainfall simulations all with different numbers of storms and spatial event structure, therefore the spatial-temporal component is also **unconditional**. However, the boundary conditions are **highly conditioned** on the river flow values at the start of the simulation (December 1st 2013) based on the observed rainfall from the year before. Hydrological observations show that both river flows and groundwater levels were around average for Somerset Levels in

November 2013 (CEH, 2013). The flooding could have been much worse if high flows were present over the Somerset Levels in November 2013 and not as impactful if they had been lower than average.

3.3. Use Case 2b: UK Drought-Heatwave 2022

Event:

During the summer of 2022, the UK experienced very dry conditions and multiple heatwaves, including reaching 40°C for the first time. This was combined with dry conditions in the 6-months leading up to the summer. There were big impacts for national infrastructure, heat mortality (approximately 2227 excess deaths), wildfires, and agriculture. In this use case, we focused on airport runway melting at Luton Airport leading to the cancellation of 100 flights. This compound event had both a multivariate and preconditioned nature.

Attribution Methodology Overview:

The main hazard input was 6-hourly average temperatures between 7:30 am and 1:30 pm over Luton Airport. To compare factual and counterfactual climates, we used a large ensemble (525 members) of climate model simulations (HadGEM3-A runs), conditioned on SST patterns from 2022. These runs are conditioned on observed seas surface temperatures, with the counterfactual ensemble members having the anthropogenic influence on SST and sea ice components removed based on information from long-term trends (Ciavarella et al., 2018). The impact metric and threshold were chosen through regression analysis of runway temperatures and local air temperatures over Luton Airport.

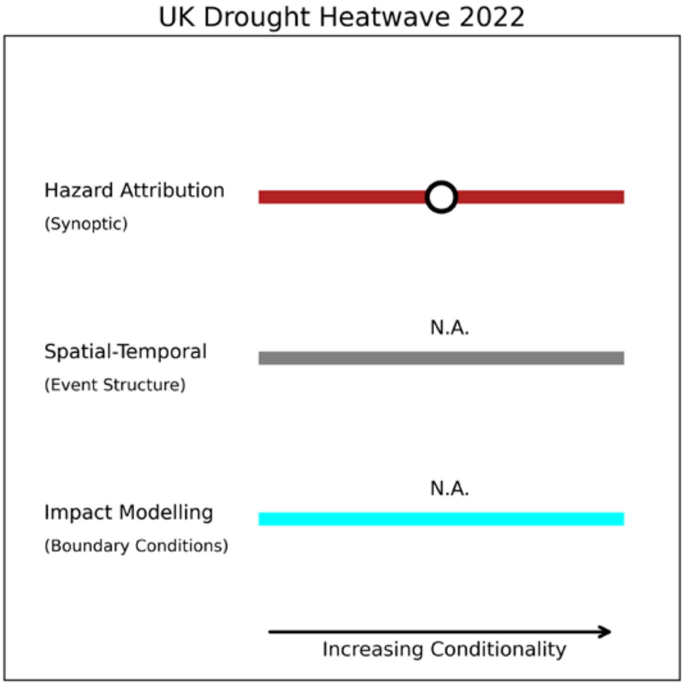

Figure 3 Compound conditionality impact attribution diagram for the UK Drought-Heatwave Use Case.

Results:

Anthropogenic climate change is found to have increased the likelihood of the runway melting by a factor of 12, with the event at least 6 times more likely and at most 32 times more likely. The intensity of the equivalent event in the pre-industrial climate is unlikely to have been hot enough for the runway to melt. The results are also consistent with other research showing low soil moisture to be a preconditioning factor in the extremity of maximum heatwave temperatures.

What are the conditional choices?

The hazard data for the attribution used both factual and counterfactual large climate model simulations for the year 2022, which were **conditioned** on SSTs for that year. SSTs around the UK had positive anomalies during the summer of 2022 (ECMWF Climate Pulse, 2025). The spatial-temporal conditioning is less relevant here, as only one location is examined for a single impact metric. The third category of conditionality did not apply to this case as there were no specific boundary conditions, such as those for more hydrological based impacts.

3.4. Use Case 3a: Tropical Cyclones Idai and Kenneth 2019

Event:

In the timeframe of six weeks, two devasting Tropical Cyclones, Idai and Kenneth hit Mozambique during the spring of 2019. TC Idai resulted in almost 1300 fatalities and impacted around 3 million people, as heavy precipitation and a combination of low-pressure and high winds lead to inland flooding and storm surges respectively. Tropical Cyclone Kenneth also brought extreme rainfall, concentrated predominantly over coastal areas, bringing severe impacts to people, transport, and agriculture. The event was both multivariate (high-winds and rainfall) and temporally compounding (consecutive strong TCs).

Attribution Methodology Overview:

The observed event was run through the relevant hydrological and hydrodynamic models in the compound flood modelling framework (Aleksandrova et al., 2024) using ERA5 and IBTrACS hazard data. The counterfactual event had estimates of anthropogenic influence on each hazard subtracted based on the long-term climate trend, which was removed as a percentage from the observed event. The rainfall estimate used the reduction from Clausius Clapeyron rate (7% increase per degree of warming), with the wind using the best estimate from the literature (10% reduction in max wind speeds). In the counterfactual scenario, the coastal water levels were reduced by 0.14m to take sea-level rise into account. TC Kenneth only examined inland flooding since coastal drivers were considered insignificant, whereas TC Idai included storm surges. Vertegaal et al. (2025) further developed the TC Idai use case and also included the wave dynamics contribution.

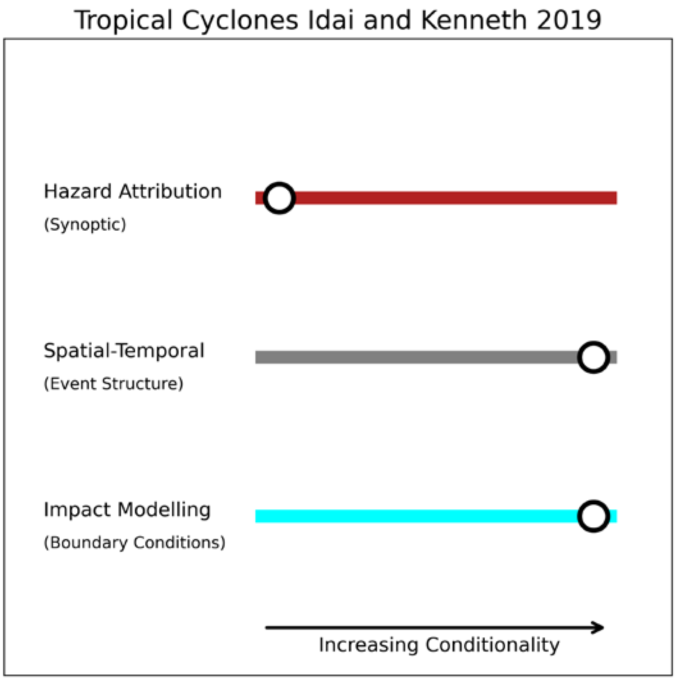

Figure 4 Compound conditionality impact attribution diagram for the Tropical Cyclones Idai and Kenneth Use Case.

Results:

Climate change is found to have led to 29% higher damages and an 18% increase in population exposed to flood depths exceeding 20 cm for TC Idai. The increase in impacts was greatest for the coastal flooding component which significantly affected the city of Beira, rather than inland flooding which contributed only a small fraction to the overall increase in impacts for this TC (Vertegaal et al., 2025). Climate change is also found to have increased the impacts of Tropical Cyclone Kenneth with a 10% increase in population exposure to 20cm flood depths or higher.

What are the conditional choices?

The hazard data for the attribution of compound flooding (Figure 4), are generally based on long term trends or results that summarize a class of events rather than a specific event (i.e. max wind speeds from literature, CC precipitation uplift), hence is an **unconditional** approach from the hazard perspective. The spatial-temporal aspect of both events, however, is **highly-conditioned** with the TC tracks are kept identical in both the factual and counterfactual. The impact modelling is also **highly-conditioned**, with the compound modelling framework conditioned on low-tides and river flows at the start of the event. This is an important point to communicate, as if the tides were not low for Idai or Kenneth; the impacts could have been much more devastating (Goulart et al., 2025).

3.5. Use Case 3b: Tropical Cyclone Freddy 2023

Event:

Tropical Cyclone Freddy brought extreme rainfall over a long-time period and with-it widespread flooding to Mozambique in 2023. The TC lasted 35 days- one of the longest on record. The flooding destroyed almost 200 000 properties, with over 1.1 million people impacted by the TC. Tropical Cyclone Freddy hit Mozambique twice after regenerating in the Mozambique channel after it hit the first time. It was a multivariate compounding event with storm surges and high precipitation occurring simultaneously.

Attribution Methodology Overview:

The observed event was run through the relevant hydrological and hydrodynamic models in the compound flood modelling framework (Aleksandrova et al., 2024) using ERA5 hazard data. Using the same methodology as in use case 3a, the rainfall increase due to Clausius Clapeyron rate (7% increase per degree of warming) was reduced from the observed event to provide the climate counterfactual, which was also simulated through the flood modelling framework.

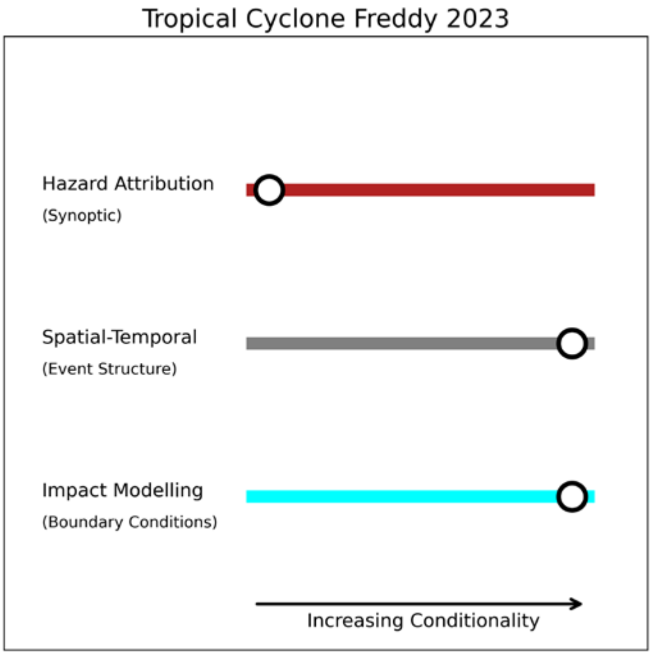

Figure 5 Compound conditionality impact attribution diagram for the Tropical Cyclone Freddy Use Case.

Results:

Climate change is found to have led to 19% higher damages and a 13% increase in population exposed to flood depths exceeding 20 cm, despite the 8% increase in rainfall intensity in the factual climate resulting in the flood extent only being 3% higher.

What are the conditional choices?

The hazard data for the attribution of flooding uses the Clausius Clapeyron rate (not representative of specific events) to produce counterfactual rainfall, and hence is an **unconditional** approach from the hazard perspective. The spatial-temporal aspect of the event, however, is **highly-conditioned** with the TC track kept identical in both the factual and counterfactual. The impact modelling was also **conditioned**, with the compound modelling framework conditioned river flows at the start of the event.

3.6. Use Case 4: Hurricanes Eta and Iota 2020

Event:

In November 2020, two consecutive hurricanes within two weeks brought severe flooding to Honduras and other countries in the region, in the form of landslides, flash flooding and riverine flooding. The hurricanes resulted in 87 fatalities and just under half a million people directly impacted, with 170 000 needing evacuation. This event was temporally compounding as Storm Iota (17th November) affected the same area, where it had rained heavily with devasting effect from Storm Eta (4th November) just 13 days earlier.

Attribution Methodology Overview:

The observed event was run through the relevant hydrological and hydrodynamic models in the compound flood modelling framework using ERA5 hazard data (Aleksandrova et al., 2024). The climate counterfactual was also run through the modelling framework, using the observed event profile from ERA5, but with rainfall intensity reduced by 9% due to the Clausius Clapeyron rate (7%/degree of warming). Both the climate factual and counterfactual included both hurricanes, with the river flow conditions at the start of Hurricane Eta.

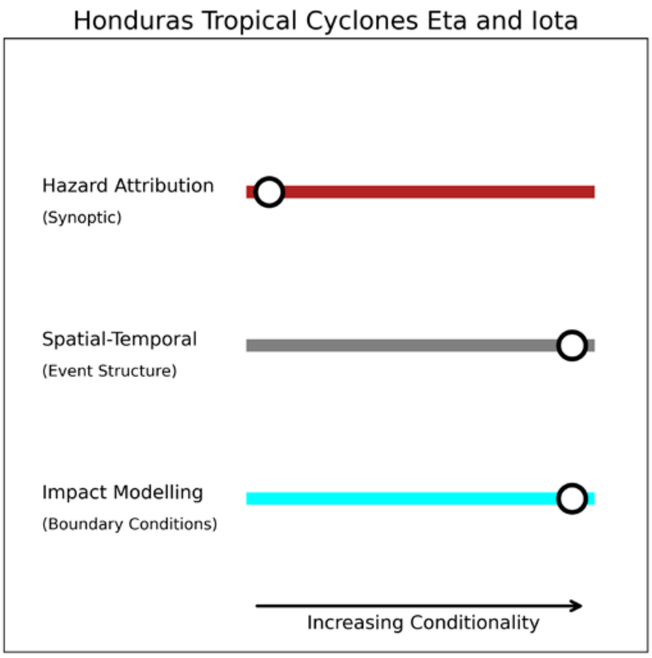

Figure 6 Compound conditionality impact attribution diagram for Hurricanes Eta and Iota Use Case.

Results:

The results showed that despite a 9% increase in rainfall intensity in the current climate, this did not translate into significantly more impacts or a larger flood extent. There were, however, limitations in the flood modeling and representation of very narrow valleys in key river systems. The differences in population and building exposure were found to be minimal between simulations of the climate factual and counterfactual run through the flood modelling framework.

What are the conditional choices?

The hazard data for the attribution of flooding uses the Clausius Clapeyron rate (not representative of specific events) to produce counterfactual rainfall and hence is an **unconditional** approach from the hazard perspective. The spatial-temporal aspect of the event, however, is **highly-conditioned** with both hurricane tracks kept identical in both the factual and counterfactual. The impact modelling was also **conditioned**, with the compound modelling framework conditioned on river flows at the start of the event.

4. Common themes across Use Cases

The six use cases show that when attribution studies are extended to impacts, they contain a wider range of choices relating to conditionality, particularly when related to complex extremes. These include choices around whether the climate signal in the hazard is based on a class of events or a specific event, whether the spatial-temporal structure remains the same, and if boundary conditions in the model that can vary (i.e. river flows/tides) remain constant or not.

Conditionality in the first category (hazard attribution) spanned from very unconditional (4 Use Cases) to partly conditioned (2 Use Cases). Three of the six studies which focused on tropical cyclones comment that most attribution methods were not suitable for their impact attributions study, given how important the exact track of the storm was for impacts and how unusual the event was. Large ensembles of climate simulations can often poorly represent peak intensities of wind and rain variables and contain too few events of the extremity required to robustly calculate anthropogenic signal. Even more conditioned approaches such as analogues and forecast attribution are potentially also not suitable, as even slight changes in the storm track could dramatically change the impacts. This is particularly true for temporally compounding events, where in cases such as Hurricanes Eta and Iota, the conditional approach would have to simulate both consecutive events without the storm track paths changing too much. The highly conditioned Climate Storyline Simulations approach (John et al., 2024) that uses spectral nudging with km-scale modelling is a promising development that could be applied to challenging events such as these. However, as found using this approach for the attribution of flooding from Hurricane Sandy there are still minor deviations in the track compared to the observed event, and the track had to be manually adjusted (Goulart et al., 2024).

Given the limited suitable methodologies available, many studies used the Clausius-Clapeyron (C-C) rate to predict rainfall intensities and hence impacts, in a counterfactual climate. This has the limitation that for many individual events the climate signal has been shown to be greater than the C-C rate (Lenderink et al., 2025). For other Use Cases, such as consecutive UK winter storms and Storm Xynthia in France, a class of events were used to derive the intensity change in the hazard due to climate change. These used either large factual and counterfactual climate simulations conditioned on sea surface temperature patterns, or extreme value analysis to extract the signal from long term trends of reanalysis data.

To go from hazard event attribution to impact event attribution, an additional choice (the spatial-temporal conditioning) was required in most of the Use Cases. For Use Cases involving coastal flooding or consecutive storm tracks, such as Tropical Cyclone Idai, Hurricanes Iota and Eta, and Storm Xynthia most studies chose to keep the spatial-temporal structure of the event the same, as without this conditioning the impacts would likely have been completely different. The impact attribution result if applying an unconditional approach to the spatial-temporal pattern, is likely to be dominated by noise from slight deviations in storm paths, rather than how climate change is influencing peak winds and rainfall within the storms. However, an understanding of how likely or unlikely the exact storm path was could also provide useful information, alongside the impact attribution results. In many cases this choice of conditionality was limited by the method used for the hazard attribution, as only in cases where ensembles of simulations are used, is there an obvious option to vary the spatial-temporal pattern. Therefore, there is a link between the conditionality choices in both the hazard attribution and spatial-temporal structure category. This category of conditionality was less relevant to impact attribution studies examining a single point location such as airport melting in the 2022 UK Drought-heatwave study. However, for use cases looking at flooding or windstorms this choice plays a major role in the results, and our interpretation of them. The windstorm component of the Storm Xynthia study kept the same spatial structure of the event for both attribution methods tested, with the results showing differences in the climate signal at different locations within the spatial-temporal structure. This is likely due to the choice of data used to produce the counterfactual, showing the benefit of using multiple attribution methods. For the UK winter storms, a range of spatial-temporal patterns were examined to produce a large enough sample of extreme events, whereas more conditioned approaches would have been challenging/expensive given that 3-month long counterfactuals would have to be produced containing 12 or more consecutive storms.

The third category of conditionality, relevant to impact attribution, are the boundary conditions used in the Use Cases. This was found to be particularly relevant to impact attribution of hydrological and coastal extremes, where tide levels and river flow values preceding the event can play a big role in the severity of the impacts. In all the Use Cases where this was relevant, these were highly conditioned to best represent the conditions before the event. This choice is natural given the case studies are impact event attribution studies. Varying these boundary conditions as well as the climate signal is significantly more work and may be unnecessary for the purpose of the study. In the case of tides, they are largely unaffected by climate change but can play a major role in the occurrence of extreme sea level, especially in regions with a large tidal range. With low tides, the flooding would not occur, and hence the attribution statement would be ill-posed. However, it is important that this aspect is discussed and communicated to stakeholders, enabling the study to address the right questions. Tropical Cyclone Idai and Kenneth both occurred while the tides were low, and TC Idai caused significant impacts from coastal flooding. If tides had been significantly higher, the impacts would likely have been even more devastating (Goulart et al., 2025). If stakeholders are interested in the study for adaptation purposes, it is important that this is communicated clearly, and in some cases, there may be value in perturbing boundary conditions to get a better overall picture of risk for the event type in question and how it is changing in a warming climate. This is of particular relevance in cases where stakeholders are interested in worst case scenarios, where an extended attribution approach could include what could have happened as well as what did happen. For Use Cases that examined windstorms or heatwave related events, this choice of conditioning was not applicable.

5. Using large-scale drivers and weather patterns for conditional attribution

Large scale drivers are defined here as predictable features of the climate system and global weather that influence weather more locally (i.e. the North Atlantic Oscillation). Conditional attribution methods are partly or fully conditioned on large-scale drivers and therefore, understanding the relationship between large-scale drivers and compound impacts, and any changes in the large-scale drivers, provides valuable context to attribution results. Additionally, if the large-scale drivers of the compound extreme in question are identified early on, this could feed into the most suitable choice of methodology for the event attribution. One of the main aims of Work Package 2 is *SO2.2: Work towards development of a framework to identify, assess and understand large scale drivers and mechanisms which give rise to compound extremes*. There were two deliverables linked to this aim:

- D2.2: Report on understanding of weather types and large-scale climate drivers (Rushby et al., 2025)
- D2.3 Dataset on weather types and large-scale climate drivers (Rushby, 2025)

The first deliverable introduces a framework developed through COMPASS to assess and understand the influence of large-scale drivers on a compound event, which is applied to the COMPASS Phase 1 Use Case 2a; the UK storms of 2013/2014 (Jack et al., 2025). An overview of the framework, the results of its application, and its potential learnings for compound attribution are summarized below.

5.1. Lessons learnt from the framework and its application in UC2a

The steps for the COMPASS framework developed in WP2 linking large-scale drivers to compound events are described in Figure 7.

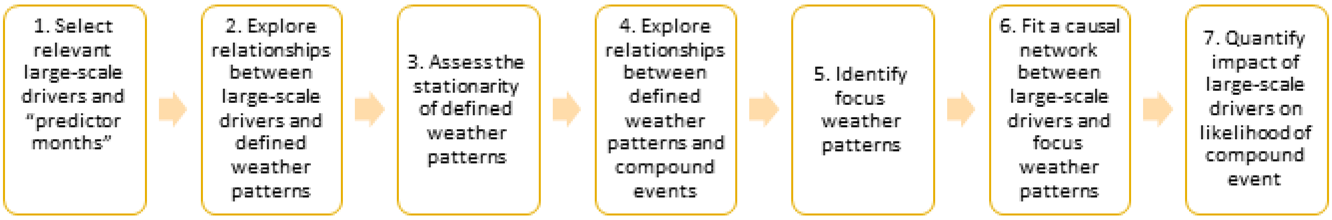

Figure 7 Framework schematic for assessing and quantifying the influence of large-scale drivers on a compound event. Figure from Rushby et al., 2025.

This framework is applied to the 2013/14 UK winter storms (UC2a), where a series of at least 12 storms within a 3-month period (Kendon and McCarthy, 2015) brought flooding of multiple types (pluvial, fluvial and coastal) to the UK. The results for each step are summarized below, including the case-specific schematic (Figure 8). For more detail on each step see Rushby et al., 2025.

Figure 8 Framework schematic for assessing and quantifying the influence of large-scale drivers on a compound event as applied to UC2a.

Step 1. Select relevant large-scale drivers and ‘predictor months’:

This step involves identifying relevant large-scale drivers for the event in question and the months over which the large-scale drivers have the most influence; these may not necessarily coincide with the months over which the event is occurring. In the case of UK winter storms, Sexton et al. (2024) identified 10 drivers with teleconnections to circulation over the UK (e.g. North Atlantic Oscillation, El Niño Southern Oscillation, Indian Ocean Dipole, and others), where monthly values for each driver were calculated from ERA5 (Sexton et al., 2025).

Step 2. Explore relationships between large-scale drivers and defined weather patterns

The 30 UK Met Office (Figure: 9) weather patterns are used both operationally in medium-range forecasting and in at least 28 peer-reviewed research papers, including climate attribution (Cotterill et al., 2022; Cotterill et al., 2024). The daily weather pattern values are produced from ERA5 daily mean sea-level pressure data over the European and North Atlantic region using k-means clustering, and are evaluated by meteorologists (Neal et al., 2016). The method used to create the patterns for the UK has also been applied to multiple other regions such as India (Neal et al., 2019), Gulf of Mexico (Steele et al., 2023) and South Africa (Ireland et al., 2024).

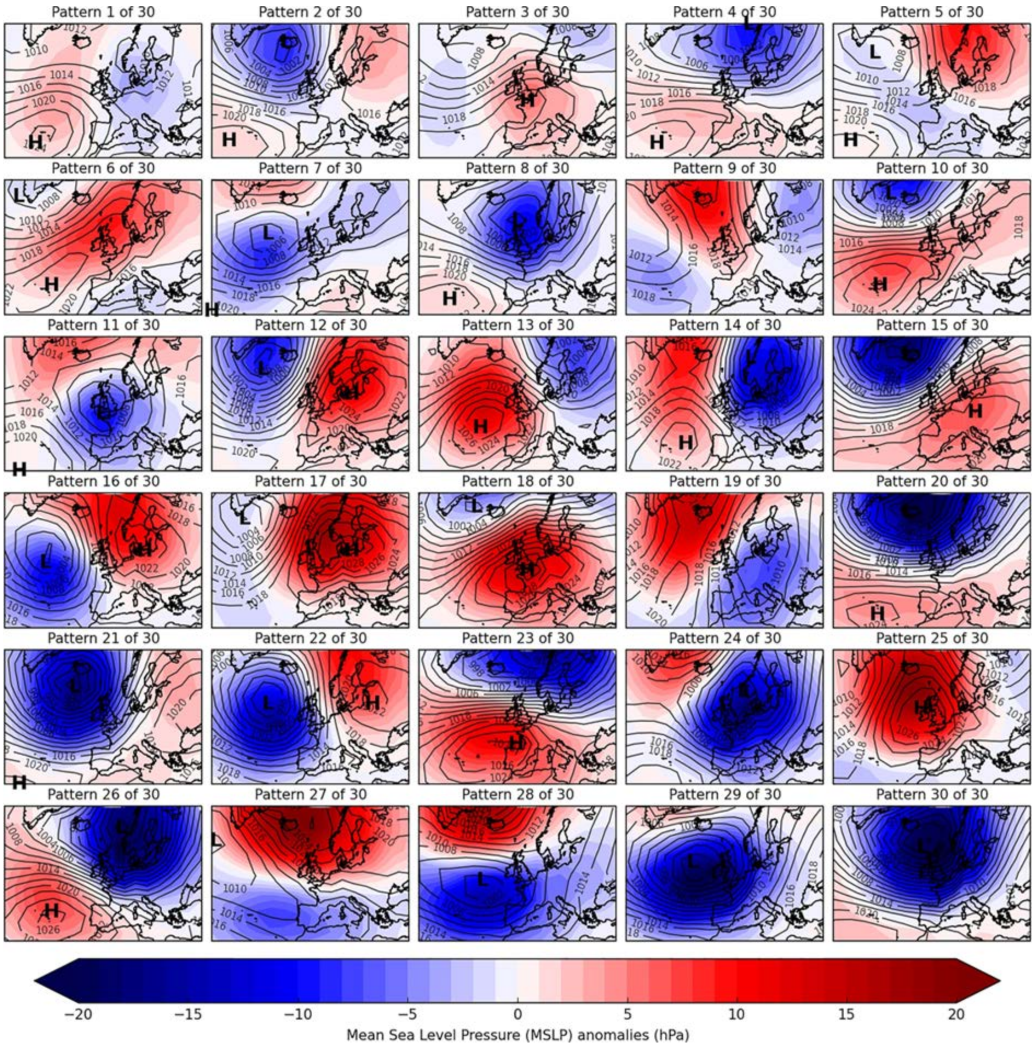

Figure 9 The Met Office 30 weather patterns defined by their mean-sea level pressure anomalies over the North Atlantic-European Domain. Figure from Neal et al., 2016.

The strength of large-scale drivers to specific weather patterns can be calculated by using the monthly index value of the large-scale drivers in Step 1, and the daily weather pattern value for each day within the month of interest (Rushby et al., 2025). For the UK winter storms case study, the frequency of each weather pattern within a month/season was assessed against the large-scale driver values identified using the causal network in Sexton et al., 2025. The results in this step showed that there were associations between specific UK weather patterns, and many of the identified large-scale drivers (Table: 2) including in January and February. This will provide useful input for step 6 of the framework.

Table 2 Summary results table of weather patterns based on daily mean sea level that have significant associations with large-scale drivers (Source: Rushby et al., 2025).

Large-scale driver	WPs with significant positive association	WPs with significant negative association
DJF AtlJet	7, 9, 11, 24, 27, 28, 29	15, 18, 20, 23, 26, 30
DJF AtleutLow	2, 16, 30	11, 14, 19, 27
DJF AtlDip	10, 11, 24, 30	22, 25, 27, 28
OND BKSIC	6, 9, 29	16, 20, 27, 28
ASO ENSO	9, 19, 24, 29	20, 21
OND IOD	4, 23, 28, 29, 30	12, 17, 27
JF NAO	10, 13, 15, 18, 20, 21, 23, 26, 30	7, 9, 11, 16, 19, 22, 24, 25, 27, 28, 29
DJF QBO	4, 13, 25, 30	11, 17, 27, 28, 29
DJF SPV	15, 20, 23, 25, 26, 30	7, 9, 11, 14, 16, 17, 24, 27, 28, 29
SON UralsMSLP	7, 11, 16, 19, 28	20, 23, 26, 29

Step 3. Assess the stationarity of defined weather patterns

Weather patterns are the chosen tool to bridge the gap between large-scale drivers and compound events, as they can be both strongly linked to large-scale drivers, and specific impacts for a region (Pope et al., 2022). For an attribution application where a changing climate is examined, it is important that the stationarity of the weather patterns is assessed; to check they are not changing significantly in spatial structure over time.

The stationarity of the 30 UK Met Office weather patterns is assessed in multiple ways using 15-year moving windows between 1979-2025 based on ERA5 data (Rushby et al., 2025). The results found that the spatial structure and intensity of some of the weather patterns within the last 40-years had changed, but that the signal was not strong enough to detect whether this is due to long-term non-stationarity or related to natural variability/methodological constraints. Therefore, although there was no detectable signal in long-term non-stationarity, Rushby et al., 2025 notes that the above should be considered whilst applying weather patterns in conditional attribution studies.

Step 4. Explore relationships between defined weather patterns and compound events

There is a significant amount of literature linking weather patterns to extreme events for a given region, including compound extremes, such as skew surge and river discharge (Hendry et al., 2019), cold-dry or cold-wet events (Mattu et al., 2025) and wind-flood events (Bloomfield et al., 2024). Rushby et al., 2025 produces a table linking different compound extremes to weather patterns for the UK, based on current literature linking 8 of the patterns to heavy precipitation and storm surges. If there is insufficient literature associating the weather patterns to the specific compound extreme of interest, an analysis could be carried out at the start of this step around the frequency of weather patterns for the compound event in question.

Step 5. Identify Focus Weather Patterns

For the case study of the UK 2013-14 storms, approximately 75% of the rainfall over the winter occurred during 3 of the weather patterns out of the 30 (Richardson et al., 2020). These were also identified as 3 of the 8 in the literature that are linked to heavy precipitation and storm surges. The two patterns linked to the highest rainfall over the case study period were weather pattern 29 and 30; these were therefore the focus patterns for step 6.

Step 6: Fit a causal network between large-scale drivers and focus weather patterns

In step 2, relationships between large scale drivers and the frequency of weather patterns in January and February were found for the UK. This step assesses the causal link between those identified large-scale drivers and the two focus weather patterns. A structural causal model, which is a set of equations used to define a causal network, is used to produce the expected frequency of the weather patterns based on immediate causal drivers and can be compared to the year-on-year frequency of each weather pattern. Therefore, when applying to the UK Winter Storms study WP 29 and 30 were predicted for the year of the event (January and February 2014).

The results showed that although there were links between the earlier identified large-scale drivers and focus weather patterns 29 and 30, the large-scale drivers did not explain most of the variability in the frequency of the focus weather patterns. Both the NAO and Atlantic Jet were identified as being statistically significant for the frequency of weather pattern 29, however, this effect was not large enough to make confident statements on the role of large-scale drivers on the 2013-14 event, with the majority of the variability in the high frequency of the focus weather patterns unexplained for the winter of 2014. Therefore, for this case study the framework was unable to produce any significant links between the large-scale drivers and the likelihood of compound extremes, and it does not progress to the final step. The report (Rushby et al., 2025) suggests that this could be due to missing drivers or conditions from the causal network, or assumptions around linearity in the model.

Step 7. Quantify impact of large-scale drivers on likelihood of compound event

This step can be applied if a strong relationship between the frequency of the focus weather patterns and large-scale drivers is found. In this case a counterfactual could be created where the large-scale drivers take average or different values, resulting in a different frequency of specific weather patterns, which are linked to compound impacts. The difference between the factual and counterfactual weather pattern frequencies and their links to compound impacts could then be used to estimate the impact of the large-scale drivers on the likelihood of the compound event. There are also many other ways in which the information from this framework can feed into compound attribution and will be covered in the discussion section below. This final step was not applied to UK Winter Storms 2013/14 in this case, given that only weak relationships were found between the relevant identified large-scale drivers and the weather patterns of interest to the compound event in the previous step.

5.2. Discussion

The framework developed can be used to directly link large-scale drivers to compound extremes using weather patterns as an intermediatory. This was applied to the 2013-14 UK Winter Storms Use Case (UC2a); however, the basic idea can be applied to other events and regions. Weather patterns have been created for multiple other regions using the method for the UK (Neal et al., 2019; Steele et al., 2023; Ireland et al., 2024). However, it does require expert judgement for the region of interest in choosing and validating the weather patterns on initial creation, as well as knowledge of the key large-scale drivers that are responsible for variability in that region.

Climate attribution studies can use methodologies that look at a class of events containing a wide range of large-scale driver conditions, or methodologies where the large-scale drivers are partially or fully fixed (conditional attribution). Multiple attribution studies already show that the level of conditioning can have an impact on the results (Buschow et al., 2024; Leach et al., 2024) even when both methods use data from the same model(s). Therefore, understanding large-scale drivers and their link to the event is incredibly important in interpreting the attribution results, and could also inform the choice of method. This is particularly pertinent if the large-scale drivers are changing over time, which is probed in the framework during the stationarity assessment.

In the case where the large-scale drivers are shown to be changing significantly over time (i.e. the weather patterns are found to be non-stationary in the observations), this framework could be used to estimate the influence of climate change on the compound event due to changes in the large-scale driver component and thermodynamic/local dynamic component individually. In this case, it would be expected that the results would differ in magnitude between more risk-based and highly conditioned attribution approaches, as highly-conditioned approaches would in many cases not take this change into account. Detection of such changes in the large-scale drivers could also help in validating climate model datasets, where to pass validation for attribution the datasets would have to reproduce the signal in the large-scale dynamics (Rushby et al., 2025).

In the case where there is no significant change in weather pattern stationarity and the large-scale drivers play a key role for the complex extreme, conditional approaches could be a better choice for the methodology for a few reasons. Firstly, it can be ensured that both factual and counterfactual data compared contain the same key drivers. Secondly, conditional approaches can reduce uncertainty in the results due to less noise resulting from natural variability in the large-scale synoptics (Buschow et al., 2024). Thirdly, less data is required than for a probabilistic approach, which is particularly beneficial for impact attribution where data is often run through computationally expensive impact models. Complex extremes require significantly more data than for univariate extremes in many cases. Therefore, the identification of focus patterns linked to compound extremes can aid some conditional attribution approaches such as analogues (e.g. Faranda et al., 2022), where analogues with these WP can be selected from large-ensembles such as SMILES. However, this may not be suitable for all compound events, especially those where the extremes are explained by antecedent conditions (pre-conditioned nature) or the intensity is explained by small-scale dynamics (Thompson 2025). In the first application (UC2a), the results showed that large-scale drivers were unable to explain the variability in the weather patterns. The next step would be to further test this framework on other complex events.

6. Summary

The work carried out in the COMPASS project through the Use Cases (Jack et al., 2025) highlights the additional complexity in conditional attribution when extending methods of single-driver hazards to impact attribution of complex extremes. Two extra strands of conditionality become relevant when applying impact attribution, which includes the spatial-temporal event structure that is simulated through the relevant impact model, and the impact model boundary conditions. These additional choices can have a large effect on the impact attribution results, and the choice of which is likely to be purpose specific. Therefore, we identify an extra need for early stakeholder engagement in impact event attribution of complex extremes so that the information provided in the study provides the most value. This is particularly relevant to hydrological related extremes.

The Use Cases also highlighted that for many event types such as Tropical Cyclones, the choice of impact attribution methodology is still very limited. Impact attribution of such events is very sensitive to the location of the storms, and therefore any methods where the storm tracks of the factual and counterfactual are not very similar become unsuitable. Therefore, either/both very highly conditioned approaches such as Climate Storyline Simulations, or hazard intensity modifications on the observed event spatial-temporal profile using values from literature are required. The former approach offers encouragement (John et al., 2024) and could provide benefit for sequential extremes such as the Use Case looking at consecutive hurricanes over Honduras. Therefore, the choice of conditionality in many cases is likely to be limited to the event type. The use cases did, however, showcase that a wide range of methodologies can be applied to complex extremes. This is the focus of and will be discussed more in *D2.7: Report on recommendations for attribution methods suitable for compound events with damaging impacts* (Cotterill et al., 2026).

In work package two of the COMPASS project, a framework linking large-scale drivers to compound extremes was developed (Rushby et al., 2025), through the usage of weather patterns as an intermediatory. Understanding the large-scale drivers for complex extremes is important in understanding and adding to the attribution results but also choosing the most suitable attribution method. Datasets used for attribution should be able to represent the most relevant large-scale drivers well for the event, with this framework providing a potential tool to test that. This framework is widely applicable to a range of locations and events, given that weather patterns use ERA5 and have been produced for multiple regions.

This report shows the complexity involved in choosing the conditionality of the attribution method when extended to impact attribution, especially in the case of complex extremes. In addition, it highlights some of the challenges around attributing specific types of complex extremes. In *D2.7: Report on recommendations for attribution methods suitable for compound events with damaging impacts* (Cotterill et al., 2026), we will look at what this means for the four types of compounding event (multivariate, temporally compounding, spatially compounding and preconditioned) as defined in Zscheischler et al., 2020, and provide recommendations of the most suitable impact attribution methods for each, building upon the learnings from the use cases and findings in this report.

References

Aleksandrova, N., Vertegaal, D., Couasnon, A., et al. (2024): Guidelines for compound extremes modelling in current and future climates. Horizon Europe project COMPASS. Deliverable D1.1.

Bloomfield, H. C., Bates, P., Shaffrey, L. C., et al. (2024). Synoptic conditions conducive for compound wind-flood events in Great Britain in present and future climates. Environmental Research Letters, 19(2), 024019. https://doi.org/10.1088/1748-9326/ad1cb7

Buschow, S., Friederichs, P., & Hense, A. (2024). Reconciling risk-based and storyline attribution with Bayes theorem. http://arxiv.org/abs/2407.10776

CEH (2013). Hydrologcial summary for the United Kingdom; November 2013. https://www.ceh.ac.uk/sites/default/files/HS_201311.compressed.pdf. Accessed: 13-12-2025

Ciavarella, A., Christidis, N., Andrews, M., et al. (2018). Upgrade of the HadGEM3-A based attribution system to high resolution and a new validation framework for probabilistic event attribution. Weather Clim. Extrem., 20, pp. 9-32, https://doi.org/10.1016/j.wace.2018.03.003.

Cotterill, D.F., Pope, J.O. & Stott, P.A. (2022) Future extension of the UK summer and its impact on autumn precipitation. Climate Dynamics, 60, 1801–1814. Available from: https://doi.org/10.1007/s00382-022-06403-0

Cotterill, D. F., Mitchell, D., Stott, P. A., & Bates, P. (2024a). Using UNSEEN approach to attribute regional UK winter rainfall extremes. International Journal of Climatology, 44(7), 2406–2424. https://doi.org/10.1002/joc.8460

Cotterill et al., 2026: Report on recommendations for attribution methods suitable for compound events with damaging impacts. Horizon Europe project COMPASS. Deliverable D2.7. DOI: 10.5281/zenodo.19047834

Coumou D, P. A. Arias, A. Bastos, et al. (2024). How can event attribution science underpin financial decisions on Loss and Damage?, PNAS Nexus, Volume 3, Issue 8, August 2024, pgae277, https://doi.org/10.1093/pnasnexus/pgae277

Deltares 2026. HORIZON COMPASS. compound-flooding-tropical-cyclones. https://github.com/HORIZON-COMPASS/compound-flooding-tropical-cyclones.

ECMWF (2025). Climate Pulse: Near real-time updates of global climate. https://pulse.climate.copernicus.eu/. Accessed: 26/11/2025

Faranda, D., Bourdin, S., Ginesta, M., et al. (2022): A climate change attribution retrospective of some impactful weather extremes of 2021, Weather Clim. Dynam., 3, 1311–1340, https://doi.org/10.5194/wcd-3-1311-2022, 2022.

Goulart, H. M. D., Benito Lazaro, I., van Garderen, L., et al. (2024): Compound flood impacts from Hurricane Sandy on New York City in climate-driven storylines, Nat. Hazards Earth Syst. Sci., 24, 29–45, https://doi.org/10.5194/nhess-24-29-2024.

Goulart, H. M., Athanasiou, P., van Ginkel, K., et al. (2025). Exploring coastal climate adaptation through storylines: Insights from cyclone Idai in Beira, Mozambique. Cell Reports Sustainability, 2(1). https://doi.org/10.1016/j.crsus.2024.100270

Hendry, A., Haigh, I. D., Nicholls, R. J., et al. (2019). Assessing the characteristics and drivers of compound flooding events around the UK coast. Hydrology and Earth System Sciences, 23(7), 3117–3139. https://doi.org/10.5194/hess-23-3117-2019

Hersbach, H., Bell, B., Berrisford, P., et al . (2020). The ERA5 global reanalysis, Q. J. Roy. Meteor. Soc., 146, 1999–2049, https://doi.org/10.1002/qj.3803.

Ireland, L. G., Robbins, J., Neal, R., Barciela, R., & Gilbert, R. (2024). Generating weather pattern definitions over South Africa suitable for future use in impact-orientated medium-range forecasting. International Journal of Climatology, 44(5), 1513–1529. https://doi.org/10.1002/joc.8396

Jack, C., Vogel, M., de Boer, T., Gale, S., et al. (2025): Hazard and Impact Synthesis and Attribution for Phase I use case. Horizon Europe project COMPASS. Deliverable D4.1.

Jézéquel, A., Dépoues, V., Guillemot, H. et al. (2018). Behind the veil of extreme event attribution. Climatic Change 149, 367–383. https://doi.org/10.1007/s10584-018-2252-9

John A., S. Beyer, M. Athanase, et al. (2024) Global Storyline Simulations at the Kilometre-scale. ESS Open Archive . DOI: 10.22541/essoar.173160166.64258929/v2.

Kendon, M. and McCarthy, M. (2015), The UK's wet and stormy winter of 2013/2014. Weather, 70: 40-47. https://doi.org/10.1002/wea.2465

Leach, N.J., Roberts, C.D., Aengenheyster, M. et al. Heatwave attribution based on reliable operational weather forecasts. Nat Commun 15, 4530 (2024). https://doi.org/10.1038/s41467-024-48280-7

Lenderink, G., de Vries, H., van Meijgaard, E., et al. (2025). A pseudo global warming based system to study how climate change affects high impact rainfall events. Weather and Climate Extremes, 100781.

Mattu, K. L., White, C. J., Bloomfield, H., & Robbins, J. (2025). Characterising Cold-Dry and Cold-Wet Compound Events in the United Kingdom. International Journal of Climatology, 45(9). https://doi.org/10.1002/joc.8859

Mentaschi L., M. Vousdoukas, E. Voukouvalas, L. Sartini, L. Feyen, G. Besio, L. Alfieri, (2016). The transformed-stationary approach: a generic and simplified methodology for non-stationary extreme value analysis. Hydrol. Earth Syst. Sci. 20, 3527–3547.

Neal R, Fereday D, Crocket R, Comer R (2016). A flexible approach to defining weather patterns and their application in weather forecasting over Europe. Meteorol Apps 23:389–400. https://doi.org/10.1002/met.1563

Neal R, Robbins J, Dankers R, et al. Deriving optimal weather pattern definitions for the representation of precipitation variability over India. Int J Climatol. (2019); 40: 342–360. https://doi.org/10.1002/joc.6215

Pope, J. O., Brown, K., Fung, F., Hanlon, H. M., Neal, R., Palin, E. J., & Reid, A. (2022). Investigation of future climate change over the British Isles using weather patterns. Climate Dynamics, 58(9), 2405–2419. https://doi.org/10.1007/s00382-021-06031-0

Richardson, D., Neal, R., Dankers, R., Mylne, K., Cowling, R., Clements, H., & Millard, J. (2020). Linking weather patterns to regional extreme precipitation for highlighting potential flood events in medium- to long-range forecasts. Meteorological Applications, 27(4). https://doi.org/10.1002/met.1931

Rushby, I., Etheridge, D., Perks, R., et al. (2025): Report on understanding of weather types and large-scale climate drivers. Horizon Europe project COMPASS. Deliverable D2.2. (Version v1). Zenodo. https://doi.org/10.5281/zenodo.17077013

Rushby, I. (2025). Dataset on weather types and largescale climate drivers (D2.3) (Version v1) [Data set]. Zenodo. https://doi.org/10.5281/zenodo.16984885

Sexton, D. M. H. (2024). Data for late winter NAO connections. In Zenodo. https://doi.org/10.5281/zenodo.10908700

Sexton, D. M. H., Yamazaki, K., Rostron, J. W., et al. (2025). Effect of resolution on simulated teleconnections to winter North Atlantic circulation inferred from a causal network derived from expert elicitation. Climate Dynamics, 63(1), 32. https://doi.org/10.1007/s00382-024-07497-4

Shepherd, T.G. (2016). A Common Framework for Approaches to Extreme Event Attribution. Curr Clim Change Rep 2, 28–38. https://doi.org/10.1007/s40641-016-0033-y

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

Steele E., Jaramillo S., Neal R., et al. (2023) "Prediction of Loop Current and Eddy Regimes in the Gulf of Mexico." Paper presented at the Offshore Technology Conference, Houston, Texas, USA, May 2023. doi: https://doi.org/10.4043/32615-MS

Thompson, V. (2025). Circulation analogues cannot identify changes in rainfall extremes. Environmental Research Letters, 20(12), 121003. https://doi.org/10.1088/1748-9326/ae20a6

Thompson, V., Ermis, S. and Athanase, M. (2025), The need for multi-method extreme event attribution. Weather. https://doi.org/10.1002/wea.7779

van Garderen, L., León-FonFay, D. The essential role of conditional attribution in understanding complex extreme weather. Nat Commun 17, 1539 (2026). https://doi.org/10.1038/s41467-026-69056-1

Vertegaal, D. M., van den Hurk, B. J. J. M., Couasnon, A, et al. (2025) (Preprint). Climate and impact attribution of compound flooding induced by tropical cyclone Idai in Mozambique. https://doi.org/10.5194/egusphere-2025-4502

Zscheischler, J., Fischer, E. M., and Lange, S. (2019): The effect of univariate bias adjustment on multivariate hazard estimates, Earth Syst. Dynam., 10, 31–43, https://doi.org/10.5194/esd-10-31-2019.

Zscheischler, J., Martius, O., Westra, S. et al. (2020). A typology of compound weather and climate events. Nat Rev Earth Environ 1, 333–347. https://doi.org/10.1038/s43017-020-0060-z.