REQUEST FOR A SPECIAL PROJECT 2024–2026

MEMBER STATE:	United Kingdom
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Other researchers:	Nicholas Leach, Sarah Sparrow, Fraser Lott, Antje Weisheimer
Project Title:	Towards an operational service for extreme weather attribution and projection

To make changes to an existing project please submit an amended version of the original form.)

If this is a continuation of an existing project, please state the computer project account assigned previously.	**SP** ………….	
Starting year: (A project can have a duration of up to 3 years, agreed at the beginning of the project.)	2024	
Would you accept support for 1 year only, if necessary?	YES X	NO ☐

Computer resources required for project year:		**2024**	**2025**	**2026**
High Performance Computing Facility	[SBU]	261,285 M	227,205 M	
Accumulated data storage (total archive volume)[2]	[GB]	316,710	592,110	

EWC resources required for project year:		**2024**	**2025**	**2026**
Number of vCPUs	[#]			
Total memory	[GB]			
Storage	[GB]			
Number of vGPUs[3]	[#]			

Continue overleaf.

[1] The Principal Investigator will act as contact person for this Special Project and, in particular, will be asked to register the project, provide annual progress reports of the project's activities, etc.
[2] These figures refer to data archived in ECFS and MARS. If e.g. you archive x GB in year one and y GB in year two and don't delete anything you need to request x + y GB for the second project year etc.
[3]The number of vGPU is referred to the equivalent number of virtualized vGPUs with 8GB memory.

Principal Investigator: Shirin Ermis

Project Title: Towards an operational service for extreme weather attribution and projection

Extended abstract

All Special Project requests should provide an abstract/project description including a scientific plan, a justification of the computer resources requested and the technical characteristics of the code to be used. The completed form should be submitted/uploaded at https://www.ecmwf.int/en/research/special-projects/special-project-application/special-project-request-submission.

Following submission by the relevant Member State the Special Project requests will be published on the ECMWF website and evaluated by ECMWF and its Scientific Advisory Committee. The requests are evaluated based on their scientific and technical quality, and the justification of the resources requested. Previous Special Project reports and the use of ECMWF software and data infrastructure will also be considered in the evaluation process.

Requests exceeding 5,000,000 SBU should be more detailed (3-5 pages).

Abstract

Many types of extreme weather events are becoming both more frequent and more severe with continuing climate change. While the field of extreme event attribution has been prolific over the past two decades in attributing anthropogenic damages for heat waves and droughts, though the picture is less clear for smaller scale events such as extreme precipitation or windstorms. Especially with the UN's ambition of compensating vulnerable nations for weather and climate damages using the Loss and Damage Fund, it becomes important to understand the impacts on dynamically driven events as well. We propose to use iteratively initialised medium-range simulations for past, present, and future climate scenarios to discern the thermodynamic impact on midlatitude cyclones. This builds on our previous work using initialised, high-resolution forecasts for event attribution on heat waves. We envision that this method can be used for operational attribution services.

Project description

Background

With rising global temperatures, devastating extreme events like heatwaves and extreme precipitation are becoming more frequent and more intense. To answer how individual events are impacted is the goal of extreme weather attribution – a science that has developed over the last two decades (Allen 2003; Otto 2017; Stott et al. 2016; Jézéquel et al. 2018). Most of the literature on attribution focusses on events with a significant thermodynamic component such as heat waves or droughts (Stott, Stone, and Allen 2004; Rahmstorf and Coumou 2011; Schiermeier 2018; *Carbon Brief* 2022). These events often impact large areas and can span multiple weeks which makes them comparatively easy to forecast.

More dynamically driven events like storms or extreme precipitation events in contrast occur on small spatial and temporal scales. Consequently, they are hard to predict multiple days or even weeks in advance. Most long-term climate simulations do not have the resolution to explicitly resolve storms and instead parameterise them, often using empirically informed relationships that typically result in large uncertainties and biases. These issues present an opportunity for models that can explicitly simulate these kinds of events, such as high-resolution, initialised medium-range weather forecasts. The challenges around resolving these events in simulations may also explain why storms, and in particular midlatitude cyclones, are little studied in event attribution (Schiermeier 2018), despite being some of the most frequent extreme events in Europe and elsewhere in the midlatitudes. Understanding changes to storm frequency and severity induced by climate change is hence an imperative for effective adaptation.

The storyline approach to event attribution was suggested by Shepherd (2016). Unlike the original approach for probabilistic attribution which compares the probability of an event *class* occurring, storyline attribution attempts to answer how climate change has altered the structure and severity of the specific event in question. A key assumption made in storyline-based attribution is that the synoptic conditions of the atmosphere, inferred by the initial conditions, can still occur in a changed climate. Given the same atmospheric state, storyline attribution then isolates the thermodynamic changes in the event due to climate change. Paired with high-resolution initialised simulations, storyline attribution can examine more dynamically unique events like cyclones or high precipitation events.

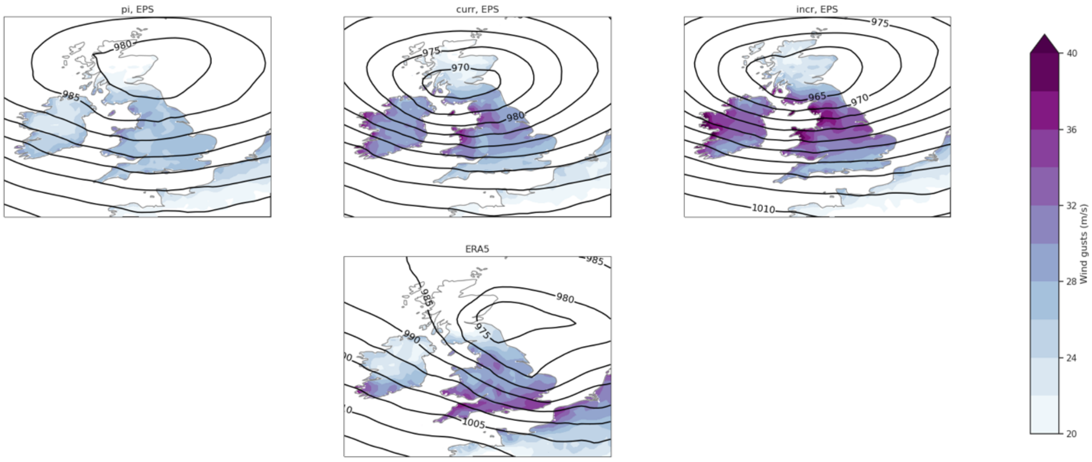

Figure 1: Changes of maximum wind gusts during Storm Eunice extreme ensemble members for initialisation at four days lead time to landfall (top row) compared to maximum wind gusts in ERA5 (bottom row). Black contours show averaged surface pressure, shading shows maximum wind gusts at each location on Feb 18, 2022.

<u>*Previous work*</u>

We previously carried out work on medium-range simulations using computing resources from ECMWF Special Projects in which the ocean temperatures as well as greenhouse gas concentrations in the atmosphere were adjusted prior to initialisation (Leach et al. 2021; Leach et al. 2022). This approach maintains the event-specificity of storyline-based attribution, while still allowing probabilistic statements to be made by looking at the evolution of the event likelihood over a range of lead times. Crucially, our approach to attribution benefits from the significant advantages made in predicting and simulating extreme weather by the weather forecasting community.

One of the key questions we posed as part of our special project for 2023 (SPGBLEAC) was whether our approach would be applicable for other types of extremes besides heatwaves. To begin to answer this question, over the past year, we have performed an attribution study on the windstorm Eunice that hit the UK on February 18, 2022. For this study, we used the same setup as before, changing the 3D ocean temperatures and salinity as well as atmospheric greenhouse gas concentrations. Despite comparatively short lead times of two to eight days, we find a significant change in the intensity of the windstorm (compare Figure 1). The predictability of the storm is not impacted which is an important precursor for the attribution study. This is a promising first result indicating that event attribution with medium-range simulations is possible for small-scale events like extra-tropical cyclones. Given that attributing such small-scale events is extremely challenging using conventional approaches to attribution, this is a considerable motivator for extending our approach further.

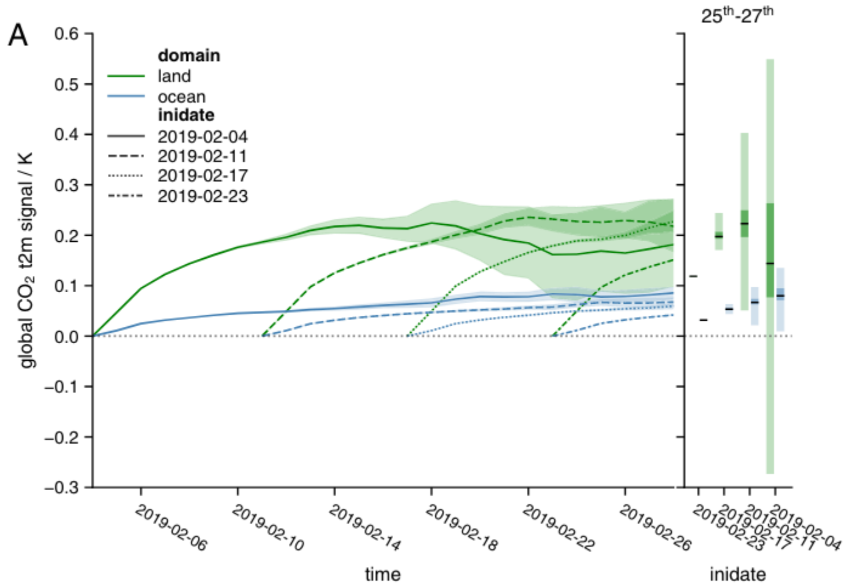

Figure 2: Response of surface temperatures to CO_2 forcing flattens off on the order of days in medium-range simulations for a winter heatwave. Green features show mean land temperatures and blue features show ocean. Line styles indicate initialization date of the experiments. In the boxplot of the temporal mean over 25 February 2019 to 27 February 2019, the black line shows the ensemble mean, dark shading indicates 90% confidence in the mean, and light shading indicates 90% confidence in the ensemble. Figure and caption adapted from Leach et al. (2021).

Present Challenges

A key outstanding question with our approach is how the lack of perturbation to the initial state of the atmosphere affects the results of our attribution studies. Using the same unperturbed initial state as in the operational (i.e., current climate) forecast means that our perturbed (pre-industrial or future climate) forecast atmosphere adjusts to the new climate throughout the model integration. This means that our experiments may not contain the complete response to human influence on the climate, but some fraction of it. This is shown in Figure 2 for surface temperatures from one of our previous studies (Leach et al. 2021) in which we only changed CO2 concentrations in the counterfactual simulations. In our previous studies on heatwaves, we addressed this issue through scaling the response by the overall mean surface temperature warming achieved in each simulation. This is physically defensible as similar thermodynamic mechanisms govern the climate change response of heatwaves and the glo§bal surface level warming. However, how to apply this scaling approach is less clear when it comes to storms. The atmospheric adjustment is likely to affect the atmospheric vertical and latitudinal temperature profile, as well as the moisture content, all of which are known to impact the genesis and intensification of midlatitude cyclones. Even though this adjustment is quite rapid (on the order of days), it may impact the storms simulated non-linearly, making the scaling approach less applicable.

This question of how to perturb the atmosphere consistently is not a new problem – though applying it to an initialised forecast is new. Most existing methods for storyline attribution remove a universal anthropogenic fingerprint for the counterfactual simulations that is independent of time and the atmospheric state, though it may be season- or month-specific. The temperature adjustments in the initial conditions can be described as

$$\Delta T = \Delta \mathrm{T}(\mathrm{k}, F_{\mathrm{cum}}),$$

where k refers to the gridbox of the model and F_{cum} are the cumulative anthropogenic forcings. It is likely that this does not reflect the actual impact of climate change on the specific state of the climate system at the time of the event of interest. Especially when analysing changes in small dynamic events, this could have a substantial impact on the severity of the event as dynamically driven extreme events are sensitively reliant on the state of the atmosphere. However, for counterfactual simulations, temperature profiles and possibly positions of large-scale dynamical features such as the jet stream need to be adjusted. Previous studies have bridged this dichotomy by using seasonal simulations (Hope et al. 2015; 2016; 2019; Wang et al. 2021) where the initial atmospheric state does not hugely influence predictability, by using spectral nudging in general circulation models (van Garderen, Feser, and Shepherd 2021; van Garderen and Mindlin 2022), by using flow analogues in reanalysis products (Yiou et al. 2017; 2020; Ginesta et al. 2022; Faranda et al. 2022), or by changing vertical temperature and moisture profiles in regional and climate models (Schär et al. 1996; Brogli et al. 2022; Pall et al. 2017; Patricola and Wehner 2018). We therefore suggest perturbations in the counterfactual that are dependent on the atmospheric state

$$\Delta T = \Delta \mathrm{T}(\mathrm{k}, F_{\mathrm{cum}}, \mathcal{W}),$$

where $\mathcal{W}$ is the weather pattern at the time of initialisation. We show this here for temperature adjustments, but it is likely necessary to adjust other variables such as specific humidity in the same way.

Apart from the atmospheric reinitialisation, there remain major challenges, especially for including changes in aerosols and the land surface, in particular soil moisture. This is the focus of a Special Project for this year, in which we are implementing adjustments in the land surface in order to more completely assess human influence on extreme weather events that can be significantly affected by land-surface processes and feedbacks, such as heatwaves or droughts. For this application, we propose to include adjustments in aerosols and an iterative approach for atmospheric adjustments in the counterfactual simulations. A system of continually calculating a ΔT (or similar Deltas for other variables) from medium-range simulations has the advantage of being physically consistent with the atmospheric state. The process itself is explained in more detail below. The approach we propose hence enables to remove anthropogenic fingerprints that are highly specific for the state of the atmosphere at any time while not requiring long-term climate projections. Ultimately, this project will help the attribution community understand better the impacts of initial conditions on weather events and move closer to operational attribution.

Scientific Plan

We aim to answer three research questions for the duration of this project.

1. How do non-CO_2 forcings like aerosols affect extreme events, in particular midlatitude cyclones?
2. What are the impacts of iteratively adjusting the atmospheric state in the counterfactual simulations?
3. Do we see the same response to climate change in other midlatitude cyclones as observed in Storm Eunice?

For the first question, we will perturb aerosol concentrations in the model initial state similar to the procedure for greenhouse gas concentrations. Since the operational version of the model uses an aerosol climatology rather than computing them interactively, we will implement aerosol perturbations by adjusting this climatology. We will be able to perturb other non-CO_2 greenhouse gases in an identical manner to CO_2.

The second question addresses our experiment setup which is a contribution towards a future operational attribution system (Wehner and Reed 2022; Stott and Christidis 2023). As outlined, we plan to iteratively nudge the counterfactual simulations towards the desired climate state. Our proposed approach is as follows:

1. Begin by initialising a counterfactual (perturbed initial condition) forecast exactly as we have done previously.
2. Choose a time *t* (on the order of a few days) at which the next counterfactual forecast is to be initialised.
3. Use the counterfactual and operational forecasts to determine the (ensemble mean) difference in the thermodynamic atmospheric fields at time *t*.
4. For the counterfactual forecast at time *t*, in addition to the ocean state perturbation and atmospheric composition changes, also perturb the atmospheric and land-surface state based on the factual-counterfactual difference at that time estimated from the previous forecast.
5. Apply this to successive forecasts in the same way.

The first few forecasts this routine is applied to still won't be in a balanced initial state, since the atmosphere will still be adjusting at time *t*. However, after this is applied to a few forecasts in a row, the measured factual-counterfactual differences between successive forecasts should stabilise. Once this stabilisation is achieved, the counterfactual forecasts should be being initialised from an approximately balanced state. In this way we would be using the physics of the model to determine what the difference between the factual initial state, and the counterfactual initial state should be at the start date of the forecast. This is conceptually quite similar to the perturbed data assimilation approach to estimate a balanced counterfactual initial state and draws upon approaches used in data assimilation elsewhere, primarily the method of breeding vectors.

To answer the final question, we plan to use this setup of simulations the full windstorm season (October to March) 2021/22. This season saw six named storms including two for which rare red weather warnings were issued by the UK Met Office, Arwen (November 26 and 17, 2021), and Eunice (February 18, 2022). Given a successful implementation of the above outlined simulations, we can perform additional attribution studies for all six storms in the season, differentiating between atmospheric changes and all other forcings.

The results from these attribution studies will then be able to inform our assessment of whether this iterative approach is suitable for operational attribution. This assessment will be dependent on the predictability of the storms within the counterfactual simulations and whether the atmospheric state in these simulations is physically consistent. We will assess whether the response to the initial condition forcing is flattening off during the simulation, minimising the model drift. This would mean that a climate representative of the counterfactual climate has been achieved.

In summary, we are planning to conduct the following simulations as part of the Special Project.

Phase	**Year**	**Steps**	**Details**
1: Non-CO_2 adjustment	2024	Estimate aerosol levels for counterfactual simulations	October to March 2021/22 with data assimilation every 3 days
		Offset ocean, greenhouse gas concentrations, and land surface as before. Add offsets in aerosol concentrations.	
		Initialise simulations every three days during the season, offsetting counterfactual simulations by the preceding difference to the factual simulation.	
2: Atmospheric adjustments	2025	Use all offsets as before and adjust the atmosphere at every data assimilation.	October to March 2021/22 with data assimilation every 3 days

Required resources

We will require enough resources to produce successive 15-day counterfactual forecasts for an extended period of time: we propose doing this for a single season. The costings of these experiments, based on the experiments we have already performed, is as follows:

Costs for testing (SBU):

1100 SBU per ensemble member per day x
1.5 scaling factor between current and ATOS computer systems (estimated using ATOS experiment hp5f) x
15 simulation days per initialisation x
51 members per initialisation x

3 types of runs (one pre-industrial climate, one present-day and one “future” for testing the linearity of the response) x
9 initialisation dates
= 34,080,750 SBU

Cost (SBU) for Year 1:

1100 SBU per ensemble member per day x
1.5 scaling factor between current and ATOS computer systems (estimated using ATOS experiment hp5f) x
15 simulation days per initialisation x
51 members per initialisation x
3 types of runs (one pre-industrial climate, one present-day and one “future” for testing the linearity of the response) x
60 initialisation dates (two dates per week for 4 months)
= 227,205,000 SBU

Cost (SBU) for Year 2:

1100 SBU per ensemble member per day x
1.5 scaling factor between current and ATOS computer systems (estimated using ATOS experiment hp5f) x
15 simulation days per initialisation x
51 members per initialisation x
3 types of runs (one pre-industrial climate, one present-day and one “future” for testing the linearity of the response) x
60 initialisation dates (two dates per week for 4 months)
= 227,205,000 SBU

Overall cost (SBU)

34,080,750 +
2x227,205,000
= 488,490,750 SBU

Cost (Storage in GB):

2.0 GB per ensemble member per day x 137,700 factors listed above x
2 (two years)
= 550,800
+ 41,310 for testing
= 592,110 GB

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