# REQUEST FOR A SPECIAL PROJECT 2026–2028

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| **MEMBER STATE:** | United Kingdom |
| **Principal Investigator[1]:** | Shirin Ermis |
| **Affiliation:** | University of Oxford |
| **Address:** | Department of Physics<br>Parks Road<br>OX1 3PJ Oxford, UK |
| **Other researchers:** | Nicholas Leach, Sarah Sparrow, Fraser Lott, Antje Weisheimer |
| **Project Title:** | Developing State-Specific Atmospheric Adjustments for Forecast-Based Event Attribution |

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. | **SPGB**ERMI | |
| Starting year: (A project can have a duration of up to 3 years, agreed at the beginning of the project.) | 2026 | |
| Would you accept support for 1 year only, if necessary? | YES x | NO ☐ |

| **Computer resources required for project year:** | | **2026** | **2027** | **2028** |
|---|---|---|---|---|
| High Performance Computing Facility | [SBU] | 64,719,000 | 51,408,000 | |
| Accumulated data storage (total archive volume)[2] | [GB] | 92,412 | 160,956 | |

| **EWC resources required for project year:** | | **2026** | **2027** | **2028** |
|---|---|---|---|---|
| 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:** Developing State-Specific Atmospheric Adjustments for Forecast-Based Event Attribution

# 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**

Extreme event attribution answers the question of how climate change impacts extreme weather events – helping us understand the risks associated with a changing climate. Over the last years, we have been developing a method for event attribution which utilises the reliability of operational weather forecasts to study extreme events. Forecast-based attribution has the advantage that it can not only assess the thermodynamic changes to an event but also begin to understand how dynamics and thermodynamic interact to change the weather. Here, we are proposing to build on previous work from special projects where we demonstrated the capabilities of forecast-based attribution for heatwaves and storms. We aim to improve the method further by perturbing the atmospheric initial conditions towards the climate change scenario we model. The novelty of our proposed approach is that is solely relies on the response of the forecast model to forcing. This addition will help make attribution statements more reliable and interpretable and help understand risks from extreme weather for policy making, infrastructure and other sectors.


**Project Description**

<u>Background</u>

With rising global temperatures, many extreme weather events such as heatwaves and storms are becoming more intense and/or frequent. Extreme event attribution is aiming to answer how events are impacted by climate change, both in frequency and severity. Over the last two decades, a variety of extreme event attribution methods have been developed. As a result, our understanding of extreme events such as heatwaves and storms has been growing – with substantial benefits for policy, infrastructure and the financial sector among many others.

The so-called storyline approach to attribution, introduced by Shepherd (2016), models the event of interest in a warmer or colder climate, keeping the dynamics of the observed event constant. With this, storyline attribution aims to isolate the thermodynamic effects of climate change on extreme weather events.

The challenge in this method is to adjust the atmosphere towards a different climate in the simulation. Different methods have found a variety of ways to solve this dichotomy (e.g. van Garderen, Feser, and Shepherd 2021; Hope et al. 2016; Athanase et al. 2024; Patricola and Wehner 2018). However, most of these methods rely on calculating a climate change fingerprint in the temperature from coarse climate model simulations such as CMIP. These fingerprints are highly uncertain as climate models do not agree on the degree of local warming or even climate sensitivity (Zhang and Chen 2021; Williamson et al. 2021).

Additionally, fingerprints are not specific for the state of the atmosphere and hence might disturb features which are important for the event of interest such as weather fronts.

Our group has previously developed the forecast-based attribution method (Leach et al. 2021; Ermis et al. 2024; Leach et al. 2024). This method uses simulations of ECMWF's Integrated Forecast System (IFS), changing the full-depth ocean temperatures and salinity in the initial conditions and adjusting the atmospheric CO2 concentrations. After the initialisation, this system is run freely, which allows us not only to study the thermodynamic effect of climate change on extremes but also the dynamic adjustment on short timescales.

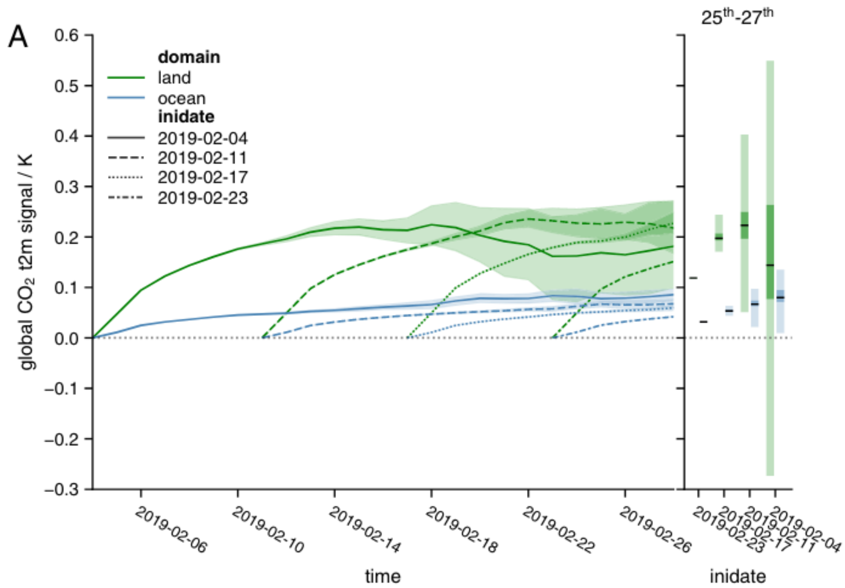


*Figure 1: Response of surface temperatures to $CO_2$ forcing flattens off on the order of days in medium-range simulations for a winter heatwave. Green features show mean land temperatures and blue features show ocean. Line styles indicate initialization date of the experiments. In the boxplot of the 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).*

<u>Previous work</u>

Using the forecast-based attribution method, and with the support of previous Special Projects, we have published attribution studies on heatwaves (Leach et al. 2021; 2024) and midlatitude storms (Ermis et al. 2024). We show that the forecasts are able to reproduce the severity of the observed events and that we are hence able to reliably estimate the effects of climate change.

In the past year, we were able to use resources from the Special Project SPGBERMI to compare three types of storyline attribution methods to the methodology used by World Weather Attribution. This work highlighted the importance of the level of synoptic freedom (or "conditioning") in simulations on the quantitative and even qualitative attribution statement. With the work we are proposing here, we aim to explore this further to make attribution statements reliable and actionable.

We have completed initial testing for including climate change perturbations in the initial conditions of the atmosphere in IFS CY47R3 and are now confident that we can implement the process suggested below. Additionally, we are currently implementing sensitivity tests which will add a climate change fingerprint obtained from ERA5 to the initial conditions of a forecast to estimate the effect that climate drift might have on our attribution statements.

<u>Present Challenges</u>

A key challenge for event attribution is to keep the dynamics of the observed event (event specificity) while adjusting large-scale dynamics to climate change. This dichotomy can never be fully resolved but methods such as forecast-based event attribution, which allow the simulations to run freely, can begin to answer questions about the dynamic impacts of climate change on extreme events. In our present setup, we are using the same unperturbed initial state as in the operational (current climate) forecast, introducing a climate drift while the atmosphere adjusts to changed CO2 concentrations and ocean temperatures. We previously analysed simulations with a range of lead times which show different levels of atmospheric adjustment (see figure 1). These simulations likely underestimate the effect of climate change on the extremes due to the spin-up period. Here, we are proposing a method that adjusts the atmosphere to climate change by iteratively adding climate change signals to a new initialisation of the forecast system.

Our proposed method would calculate differences between the factual and counterfactual forecasts in intervals of up to 24 hours, creating climate change adjustments that are specific for the synoptic conditions and to the IFS model, thereby avoiding model drift.

A system of continually calculating a climate change signal 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**

As outlined in our previous work, we plan to iteratively adjust 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 an iteration window (on the order of a few hours) 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 after the iteration window.
4. For the counterfactual forecast after the iteration window, in addition to the ocean state perturbation and atmospheric composition changes, also perturb the atmospheric 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, will not be in a balanced initial state, since the atmosphere will still be adjusting after the first iteration window. However, after this is applied to a few forecasts, the measured factual-counterfactual differences between successive forecasts should stabilise. Once this stabilisation is achieved, the counterfactual forecasts will be initialised from an approximately balanced state. In this way we will use 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 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. A graphic of this method is shown in figure 2.

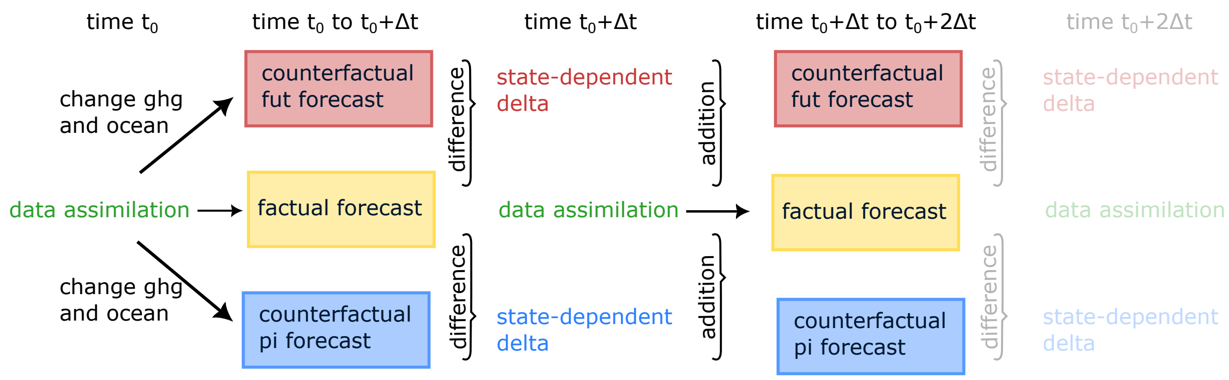


*Figure 2: Graphic representation of the proposed iterative atmospheric adjustment for forecast-based attribution. In the first step, only CO2 and ocean states are perturbed in the counterfactual forecasts. After the first iteration window Δt the difference between the factual and counterfactual forecasts is calculated and added to the next iteration.*

To implement this method, we intend to test the effects of both the iteration window, and the lead time to the event. For the iteration window, we will test lengths of 12 hours and 24 hours. We assume that longer iteration windows would disturb the initial states too much through model error causing divergence between the factual and counterfactual initial state. The lead time to the event (here including the reinitialization of forecasts, so not just one simulation) will be set to 1, 2, 4, and 8 weeks in a second step.

We propose to test the setup initially on one extreme event, such as Storm Eunice from 2022. Once a reliable setup has been identified, we aim to study three different types of extreme events with it

In summary, we are planning to run the following simulations across two years.

| ***Phase*** | **Year** | **Steps** | **Details** |
|---|---|---|---|
| *1: Test parameters of the attribution setup* | 2026 | Test the effect of varying the length of the iteration window. | Test 12-hour and 24-hour windows, 24-hour integrations, 14-day lead time to the event |
| | | Test the effect of varying the length of the lead time to the event. | Test 1, 2, 4, and 8 weeks lead time to the event with 12-hourly reinitialisation |
| *2: Case studies* | 2027 | Run case study simulations with the attribution setup from Phase 1 | Maximum computing resources of 112 initialisations of 24 hours for three events |

**Required Resources**

<u>Cost (SBU) for testing</u>

1500 SBU per day per ensemble member (estimated for CY48R1 at 18km in 2024) x

5-day iteration per simulation x

51 ensemble members x

10 initialisation dates x

3 types of runs (preindustrial, current, future climates)

= 11,475,000 SBU

Cost (SBU) for Year 1

Testing iteration time step

1500 SBU per day per ensemble member (estimated for CY48R1 at 18km in 2024) x

1-day iteration per simulation x

51 ensemble members x

(28 + 14) initialisations x

3 types of runs (preindustrial, current, future climates)

= 9,639,000 SBU

Testing for lead time

1500 SBU per day per ensemble member (estimated for CY48R1 at 18km in 2024) x

1-day iterations per simulation x

51 ensemble members x

(14 + 28 + 56 + 112) initialisation dates x

3 types of runs (preindustrial, current, future climates)

= 48,195,000 SBU

Cost (SBU) for Year 2

Running all events with final setup

1500 SBU per day per ensemble member (estimated for CY48R1 at 18km in 2024) x

1-day iterations per simulation x

51 ensemble members x

112 initialisation dates x

2 events x

3 types of runs (preindustrial, current, future climates)

= 51,408,000 SBU

Overall cost (SBU)

Year 1: 69,309,000 +

Year 2: 51,408,000

= 120,717,000 SBU

Storage (in GB)

Year 1

2 GB per ensemble member per day x
(126 + 630) simulation days above x
51 ensemble members x

= 77,112 GB

+ 15,300 GB for testing

= 92,412 GB

Year 2

2 GB per ensemble member per day x
(126 + 630 + 672) simulation days above x
51 ensemble members x
= 145,656 GB
+ 15,300 GB for testing
= 160,956 GB

**References**


Athanase, Marylou, Antonio Sánchez-Benítez, Eva Monfort, Thomas Jung, and Helge F. Goessling. 2024. 'How Climate Change Intensified Storm Boris' Extreme Rainfall, Revealed by near-Real-Time Storylines'. *Communications Earth & Environment* 5 (1): 676. https://doi.org/10.1038/s43247-024-01847-0.

Ermis, Shirin, Nicholas J Leach, Fraser C Lott, Sarah N Sparrow, and Antje Weisheimer. 2024. 'Event Attribution of a Midlatitude Windstorm Using Ensemble Weather Forecasts'. *Environmental Research: Climate* 3 (3): 035001. https://doi.org/10.1088/2752-5295/ad4200.

Garderen, Linda van, Frauke Feser, and Theodore G. Shepherd. 2021. 'A Methodology for Attributing the Role of Climate Change in Extreme Events: A Global Spectrally Nudged Storyline'. *Natural Hazards and Earth System Sciences* 21 (1): 171–86. https://doi.org/10.5194/nhess-21-171-2021.

Hope, Pandora, Guomin Wang, Eun-Pa Lim, Harry H. Hendon, and Julie M. Arblaster. 2016. 'What Caused the Record-Breaking Heat Across Australia in October 2015?' *Bulletin of the American Meteorological Society* 97 (12): S122–26. https://doi.org/10.1175/BAMS-D-16-0141.1.

Leach, Nicholas J., Christopher D. Roberts, Matthias Aengenheyster, Daniel Heathcote, Dann M. Mitchell, Vikki Thompson, Tim Palmer, Antje Weisheimer, and Myles R. Allen. 2024. 'Heatwave Attribution Based on Reliable Operational Weather Forecasts'. *Nature Communications* 15 (1): 4530. https://doi.org/10.1038/s41467-024-48280-7.

Leach, Nicholas J., Antje Weisheimer, Myles R. Allen, and Tim Palmer. 2021. 'Forecast-Based Attribution of a Winter Heatwave within the Limit of Predictability'. *Proceedings of the National Academy of Sciences* 118 (49): e2112087118. https://doi.org/10.1073/pnas.2112087118.

Patricola, Christina M., and Michael F. Wehner. 2018. 'Anthropogenic Influences on Major Tropical Cyclone Events'. *Nature* 563 (7731): 339–46. https://doi.org/10.1038/s41586-018-0673-2.

Shepherd, Theodore G. 2016. 'A Common Framework for Approaches to Extreme Event Attribution'. *Current Climate Change Reports* 2 (1): 28–38. https://doi.org/10.1007/s40641-016-0033-y.

Williamson, Mark S., Chad W. Thackeray, Peter M. Cox, Alex Hall, Chris Huntingford, and Femke J. M. M. Nijsse. 2021. 'Emergent Constraints on Climate Sensitivities'. *Reviews of Modern Physics* 93 (2): 025004. https://doi.org/10.1103/RevModPhys.93.025004.

Zhang, Shaobo, and Jie Chen. 2021. 'Uncertainty in Projection of Climate Extremes: A Comparison of CMIP5 and CMIP6'. *Journal of Meteorological Research* 35 (4): 646–62. https://doi.org/10.1007/s13351-021-1012-3.