University of Reading

The concept of spectrally nudged storylines for extreme event attribution

Article

Published Version

Open Access

Feser, F. and Shepherd, T. G. ORCID: https://orcid.org/0000-0002-6631-9968 (2025) The concept of spectrally nudged storylines for extreme event attribution. Communications Earth and Environment, 6. 677. ISSN 2662-4435 doi: 10.1038/s43247-025-02659-6 Available at https://centaur.reading.ac.uk/123774/

It is advisable to refer to the publisher's version if you intend to cite from the work. See Guidance on citing.

To link to this article DOI: http://dx.doi.org/10.1038/s43247-025-02659-6

Publisher: Nature

All outputs in CentAUR are protected by Intellectual Property Rights law, including copyright law. Copyright and IPR is retained by the creators or other copyright holders. Terms and conditions for use of this material are defined in the End User Agreement.

www.reading.ac.uk/centaur

CentAUR

University of Reading

Central Archive at the University of Reading

Reading's research outputs online

communications earth & environment

Perspective

A Nature Portfolio journal

https://doi.org/10.1038/s43247-025-02659-6

The concept of spectrally nudged storylines for extreme event attribution

Check for updates

Frauke Feser [1] & Theodore G. Shepherd [2,3]

Spectrally nudged storylines (constraining the large-scale atmospheric circulation to follow that of a particular weather event) represent a relatively new attribution method. They differ from conventional, probabilistic attribution approaches which consider a class of similar, generally univariate, extremes. Instead, their focus is on particular, historic extreme events of large impact which are still vividly anchored in collective memory. The innovation of the method is the feasibility to quantify the role of anthropogenic climate change for specific extreme events of the recent past, and it draws on experience from regional climate downscaling. Spectrally nudged storylines thus offer a new, easily implemented and easily understandable way of communicating climate change to the general public and decision-makers, as well as a pathway for detailed attribution of climate impacts. The technique offers great potential as an addition to the established attribution methods by answering different questions and providing new attribution results.

Extreme weather events have a large impact on population, economy, infrastructure, agriculture and ecosystems. The attribution of these events to climate change is a relatively new scientific field and only emerged during the last decades[1]. The reason for this is that in classical climate-change science, attribution of an observed phenomenon to anthropogenic climate change requires demonstrating that the phenomenon is both consistent with anthropogenic climate change and inconsistent with any other explanation[2]. This classical approach generally fails in the case of single extreme events, because of the large role of internal variability. Palmer and Räisänen[3] therefore suggested replacing the strong form of classical climate attribution with a weaker form, where it is only required to demonstrate that anthropogenic climate change made the event more likely. In general terms[4], this can be seen as replacing specific causation (the actual cause of a specific event) with general causation (the potential to cause the specific event). Thereby, the statistics of an event are compared as it was observed under present climate (so-called 'factual' conditions), including climate change, to its corresponding statistics in a 'counterfactual world' without anthropogenic climate change. If the event was made more likely, e.g., as estimated by a risk ratio, then it is attributed to anthropogenic climate change, in this weaker sense of general causation. This has now become the conventional approach to event attribution[5].

There are at least two inherent limitations of this conventional, probabilistic approach. The first is that a statistical population must be constructed, whereby the specific event is replaced by a much broader 'event class', which is typically univariate. Yet the impacts of the event, which are normally the reason for the interest in the event, can be quite sensitive to the particular details of the event. That is why it is widely understood in statistics that inferences concerning statistical populations cannot be reliably applied to individual members of those populations[6]. The second limitation is that even this weaker form of attribution relies on a clear climate change signal, which is generally obtained from climate models, and which can be ambiguous because of the deep uncertainties in the dynamical response to climate change at the local scale[7]. To address both of these limitations, Trenberth et al.[8] suggested that distinguishing between dynamic and thermodynamic factors could lead to less uncertainty in the attribution of extreme events. In particular, they proposed treating the dynamical conditions leading to the event as given, and asking how the thermodynamic consequences of the event (e.g., heavy precipitation) were affected by known aspects of climate change, such as warming of sea-surface temperatures (SSTs). It was argued that the inclusion of this established scientific knowledge on climate change increases the signal-to-noise ratio and thus leads to a more reliable attribution result (see also Shepherd[9], who dubbed it the 'storyline' approach). Lloyd and Oreskes[10] noted that the storyline approach could be seen as guarding against false negatives (i.e., failing to detect the consequences of climate change), whilst the conventional approach guarded against false positives. Thus, both had their scientific purposes.

To implement the storyline approach in a climate model, one needs to be able to re-simulate specific extreme weather events which happened in the recent past under different climate conditions. For that, some kind of constraint on the model's dynamics is needed. This is essential, because initially similar dynamical states will diverge in time through chaos, a phenomenon known as the 'butterfly effect'[11]. Therefore, to follow an

[1]Institute of Coastal Systems, Helmholtz-Zentrum Hereon, Geesthacht, Germany. [2]Department of Meteorology, University of Reading, Reading, UK. [3]Jülich Supercomputing Centre, Forschungszentrum Jülich, Jülich, Germany. e-mail: frauke.feser@hereon.de

Table 1 | Frequently asked questions about Spectrally Nudged Storylines, based on the authors' experience

Frequently asked questions	
What are Storylines?	Storylines are causal explanations where some of the explanatory factors may be contingent, i.e., considered as accidental. In storyline extreme event attribution, the dynamical set-up of the event is treated in this way.
Why do we need strongly conditioned attribution methods in addition to probabilistic methods?	The two methods are complementary, and answer different attribution questions[59].
Storylines versus Digital Twins?	Digital Twins replicate physical systems or components, updated with real-time data. For the climate system they are essentially data assimilation systems, extended into the impact domain. In principle, Digital Twins could be used in a storyline framework.
Is Spectral Nudging violating physical conservation laws?	Yes, this is true of any model intervention, including data assimilation. On the other hand, it ensures that the simulation is physically realistic since it minimizes model bias.
What is the difference between Storyline and Climate Scenario Simulations?	They are both conditional predictions, but the conditioning level is very different. For scenarios the conditioning is on future levels of anthropogenic emissions and land use. For physical climate storylines, the conditioning is on global warming levels and specific circulation features. So far, physical climate storylines are mainly either of extreme events (event storylines) or of remote drivers of regional climate (dynamical storylines; see below). See box 10.2 in Ref. 60.
What is the difference between Spectrally Nudged and Dynamical Storylines?	Spectrally Nudged Storylines are one implementation of strongly conditioned (event) storylines. Dynamical Storylines is the term commonly used for the regional climate changes arising from storylines of remote drivers of regional climate. They are derived statistically from climate model output rather than through model intervention.
What are the advantages of Spectrally Nudged Storylines?	Changes of extreme events which are anchored in collective memory of a region can be simulated. Better understanding of the local effects of climate change compared to climate scenarios. They allow for robustness tests of adaptation measures.

extreme event through its entire evolution, the model needs some additional enforcement to stay close to observations, beyond the initial or lateral boundary conditions. A popular method to fulfil this task is spectral nudging. It constrains the large spatial scales of a climate model within the free atmosphere (i.e., outside of the boundary layer) so that it is 'nudged' towards, for instance, reanalysis data. The technique was first adapted and applied to regional climate models at the GKSS research centre[12] (today Helmholtz-Zentrum Hereon) after the idea emerged in the 1990s for weather models[13]. At a storm workshop in Reading in 2017, the authors started to develop the idea to combine their methods, namely storylines and global spectral nudging, to a new extreme event attribution technique called spectrally nudged storylines.

This article provides a perspective on how the storyline and spectral nudging methods were combined to spectrally nudged storylines as a new method of attributing extreme weather events to anthropogenic climate change. We show how the spectral nudging technique was established and evolved over time, for a variety of different purposes. What these different purposes have in common is the need to constrain the butterfly effect in order to answer a particular, conditional scientific question, where the large-scale flow can be reasonably regarded as given. Then we elaborate on the development and details of spectrally nudged storylines and review studies that use these methods. Spectrally nudged storylines are discussed in comparison to other strongly conditioned attribution methods, and first approaches are presented that apply spectrally nudged storylines for impact studies. We conclude with an outlook on further applications of spectrally nudged storylines given current developments in climate science.

A list of frequently asked questions on the method, subjectively assembled by the authors, is provided in Table 1 below. Since this kind of storyline attribution is a recent innovation, only a limited number of studies exist so far. However, we believe that the new attribution method adds valuable information for extreme event attribution and will improve communication about climate change and its impacts. Instead of providing generalized probabilities based on abstract model ensembles, the method gives readily interpretable answers to practical questions such as 'What if this same extreme event happened in a warmer or cooler climate and how large is the human impact?'.

Spectral nudging for climate models

The term 'spectral nudging' was first introduced by Waldron et al.[13] to describe the imposition, through an extended Newtonian relaxation approach, of the large-scale weather patterns of a global atmospheric model throughout the domain of a limited-area weather forecasting model. Independently of this work, von Storch et al.[12] developed spectral nudging for regional climate model simulations. In both cases, the method was developed for technical reasons, as an add-on to the standard method of constraining the large scales of a regional weather or climate model only through the lateral boundary conditions, as constraining only the lateral boundary conditions can lead to internal states inconsistent with the driving fields. Spectral nudging is applied for only a very few variables, specifically horizontal wind components or divergence and vorticity, and in the free atmosphere, to allow the lower atmosphere, and smaller-scale features, to respond to perturbations in a dynamically consistent way. It is called spectral, as the nudging is applied only for large spatial scales, for instance just for the low wavenumbers of a spectral model. (For grid point models a Fourier transformation is applied, to connect grid point space to wavenumber space.) The rationale behind the method (which can be verified a posteriori) is that local meteorological conditions are determined by a combination of the large-scale flow (provided by the nudging) and the details of the surface physics (provided by the model). Weisse and Feser[14] showed that for ensemble simulations for wind hindcasts with and without spectral nudging using slightly disturbed starting conditions, spectral nudging reduces the internal model variability and leads to smaller differences to observations on average, compared with solely constraining the regional model through the lateral boundary conditions. In other words, it constrains the butterfly effect.

Von Storch et al.[12] noted that spectral nudging could be seen as a "poor person's data assimilation technique," and thus was also a way of producing regional reanalyses, even without regional observations, using the regional model to fill in the physical detail. A large number of studies subsequently applied spectral nudging for dynamical downscaling of large-scale reanalysis data to produce long-term regional hindcasts of climate variability[15]. Of course, there is nothing to prevent applying spectral nudging within a global model[16]; the rationale in that case has nothing to do with lateral boundary conditions but instead has to do with avoiding temporal inhomogeneities that can arise from the assimilation of varying numbers of measurement data in reanalyses over time. In a similar spirit, spectral nudging can be used to validate a model against sparse observations, by ensuring that the comparison is 'like for like'[17]. Importantly, all of these studies emphasize that the nudging must be carefully adjusted for the purpose at hand, since too strong nudging can lead to a dampening of regional processes, whilst too weak

Table 2 | Example of the complementary attribution statements that are possible using the probabilistic and storyline approaches, for the case of the 2010 Russian heat wave (Table from van Garderen et al.[18])

Probabilistic attribution (based on results from ref. 61)	Averaged over the Russian domain and over the month of July, temperatures in 2010 were 5 °C above the 1960s climatology, of which 4 °C was due to internal variability and 1 °C was due to anthropogenic climate change. The heatwave represented a 1-in-33 year event, which was three times more likely than it would have been in the 1960s.
Storyline attribution (based on results from ref. 18)	Averaged over the Russian domain, temperatures in 2010 steadily increased from the 1985–2015 climatology through the month of July until about August 10, then rapidly returned to climatology. The domain-averaged heatwave reached 10 °C above the 1985-2015 climatology in early August, of which 8 °C was due to internal variability and 2 °C was due to anthropogenic climate change. The anthropogenic component of the warming reached 4 °C in the region to the south of Moscow during the first half of August, where it exacerbated the already warm temperatures there.

nudging can fail to sufficiently constrain the large-scale flow. More details on choosing the nudging settings can be found in the Supplementary and in refs. 16,18.

Relevant to our purpose here, spectral nudging has also been used for the attribution of causal effects. Here, the global model is run twice, once with and once without the causal effect. If the model was run freely, then the butterfly effect would mean that differences between the two simulations would not necessarily reflect the causal effect, but could also reflect internal variability. Overcoming this ambiguity by performing a large ensemble of simulations would return us to the previously discussed problems associated with probabilistic event attribution. In contrast, spectral nudging provides a direct causal estimate that is conditional on the imposed atmospheric state. For example, Kooperman et al.[19] used spectral nudging to estimate the aerosol indirect effect, although the nudging was to a climate model simulation rather than to reanalysis. A closer parallel to extreme event attribution is Shepherd et al.[20], who applied spectral nudging within a chemistry-climate model to attribute the role of halogen-induced stratospheric ozone loss in the observed record of global ozone. Because the observed record includes a strong component of natural variability, the set-up was able to resolve a number of outstanding scientific puzzles, e.g., where anomalous dynamical variability had masked chemical ozone loss. The attribution relied on the assumption that the effect of halogen-induced ozone loss on stratospheric circulation could be neglected in the interpretation of the ozone record, which is a reasonable assumption outside of the Antarctic ozone hole region.

Spectrally nudged storylines

The method of spectrally nudged storylines was introduced independently by Refs. 18,21, applied to heat waves. The method uses a global atmospheric climate model wherein the large-scale atmospheric weather patterns are nudged towards reanalysis data so that observed extreme events can be simulated in different climate states. (A necessary first step for any attribution is to confirm that the factual simulation can closely follow the event in question.) Between the individual storylines only those external parameters are changed that were influenced by anthropogenic forcing with high certainty, notably SSTs and greenhouse gases. (Modifying sea-ice concentrations is tricky because of the need to ensure physical consistency with the modified SSTs, so is handled on a case-by-case basis and may not be necessary. Note that the same issue arises with probabilistic attribution using atmospheric models, where the sensitivity to the sea-ice counterfactual will be much more consequential because of the response of the atmospheric circulation to the sea-ice modification.) In this way, the method keeps the dynamical conditions similar between storylines, while a focus is put on the thermodynamic responses to the imposed forcings, such as warming and increased specific humidity, which are provided by the model physics and which are the robust aspects of climate change[7]. Van Garderen et al.[18] used a small ensemble of three members for each storyline to show that such a conditional attribution can lead to high signal-to-noise ratios and thus a higher confidence in the attribution, compared to the conventional, probabilistic approach. Examples of the different kinds of attribution statements provided by the two approaches are given in Table 2[18]. A variant on this approach is to allow the SSTs to respond interactively to the changed greenhouse gases, whilst maintaining the nudging of the atmospheric state[22].

The summer heat wave of 2022 over Europe was analysed by Feser et al.[23]. The study combined spectrally nudged storylines and a statistical cluster analysis of a 2000-year paleo simulation and reanalysis data to attribute the heat wave and put the extreme event into historical context. The main result is that anthropogenic climate change increased the heat wave by 1.25 °C on average and locally by up to 5.7 °C (Fig. 1). Although the present-day storyline does not exactly match the reanalysis due to model biases, the day-to-day variations are highly correlated, and it is the difference between storylines that matters. This illustrates how the storyline approach quantifies the distributions of differences (conditional specific causation) rather than the differences of distributions (general causation) considered in the conventional approach. The statistical analysis of a multimillennial paleo climate simulation confirmed that it was one of the most extreme heatwaves of the last 2000 years. This article outlines a first comprehensive approach or common framework to combine both the conventional statistical climate attribution and storyline attribution. In this way, different questions such as 'How would the heat wave have evolved under different climate conditions?' and 'How extreme was the heat wave within the last millennia?' can be answered.

The method of spectrally nudged storylines can be applied not just to medium-term events such as heat waves, but also to long-term events such as droughts and to short-term events such as heavy rainfall, all within a seamless modelling framework. Van Garderen and Mindlin[24] examined the 2011/2012 drought in southeastern South America, which had devastating impacts. Climate change has already clearly led to higher temperatures and thus to increased evaporation/evapotranspiration of water from vegetation, soil and water surfaces. On the other hand, climate change is causing more precipitation in this region, albeit in the winter season. The study showed that so far, but also in a 2 °C warmer world, this additional winter precipitation more than compensates for the increased summer evaporation. Whether this will also be the case as temperatures continue to rise, or whether evaporation will then dominate, is still unclear. This article was particularly interesting as a showcase for the potential of spectrally nudged storylines, as the interplay between larger winter precipitation offsetting the increasing summer drought potential would not have been captured with a drought index based on summer meteorological conditions alone.

In terms of heavy rainfall, a near-real-time storyline set-up was used to examine the extreme rainfall and subsequent flooding from storm Boris over Central and Eastern Europe in September 2024[25]. This study shows that a near-real-time attribution is feasible with spectrally nudged storylines, given the ease of their implementation. Recently, John et al.[26] applied the approach in a global climate model at a kilometre-scale resolution. This study represents a new step in very high-resolution storyline attribution, reaching convection-permitting scales in a global setting. In this regard, spectrally nudged storylines could lead to improved attribution results for extreme events that are more heterogeneous or of smaller spatial extent such as extreme convective precipitation, mesoscale systems or intense cyclones. Such simulations have a massive demand in high performance computing power and storage space, making them completely infeasible for probabilistic attribution, but at least within reach for the storyline approach.

A very recent development are regional spectrally nudged storylines and only a few studies applying them so far exist. Ref. 27 examined the

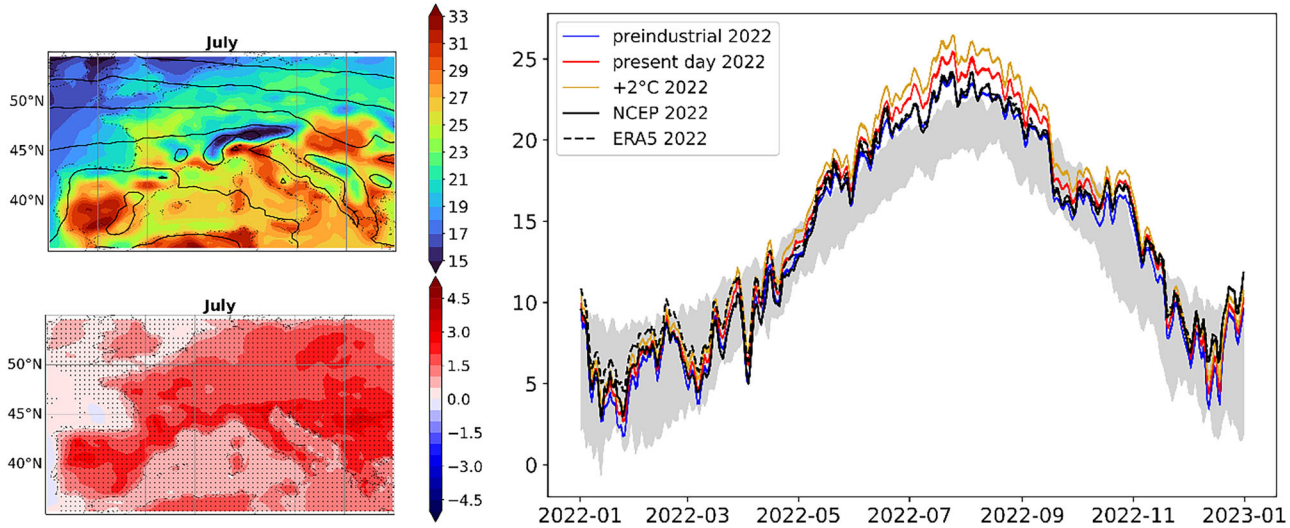

Fig. 1 | Storyline attribution of the European heatwave 2022. Left: The upper panel shows the 2 m temperatures [°C] (shaded) and present-day storyline geopotential height at 500hPa [m] (black contours) for July 2022. The lower panel shows the differences in 2 m temperature [°C] between the present-day and preindustrial simulations as shaded fields. Stippling indicates where all present-day ensemble members are > 0.1 °C above all preindustrial members for that grid point. Right: Daily mean 2m-temperature [°C] averaged over Europe (35–55°N, 10°W–25°E) for summer 2022 for the preindustrial (blue), present-day (red) and +2 °C (yellow) simulations and ERA5 (black stippled line) and NCEP (black solid line) reanalysis data. The climatology (grey shaded area) is the 5th–95th percentile range between 1985-2015 calculated with the general circulation model ECHAM[16]. Figure adapted from Feser et al.[23].

European summer heat wave of 2019, using global storylines spectrally nudged to reanalysis data which were dynamically downscaled using a regional climate model. The regional storylines showed a more intense, longer lasting and spatially extended heat wave for future climate states due to human-induced climate change. Another recent study[28] used spectral nudging to conduct thermodynamic global warming simulations for the continental US with a regional climate model. The resulting multi-decadal data set for present-time conditions and several future warming trajectories is openly available and seems to be an interesting data base for attribution applications. This is a return to the origins of spectral nudging, which as noted earlier was first developed for downscaling of climate change via regional models, but now applied in a storyline context to focus on particular kinds of extreme events. This new attribution approach offers the possibility to attribute extreme events of smaller spatial scale than heat waves and droughts, such as storms or intense precipitation events, without having to run a global high-resolution model.

Strongly conditioned attribution methods

As discussed in Ref. 9, the key ingredient is constraining the large-scale atmospheric circulation so as to distinguish between the dynamic and thermodynamic contributions to an extreme event. Ref. 1 refers to this as 'strongly conditioned attribution', since probabilistic attribution often also involves some level of conditioning, e.g., on SST patterns. Importantly, in strongly conditioned attribution the dynamical component is not ignored, but is treated separately because of the different level of uncertainty associated with dynamical aspects of climate change. There are two basic ways of constraining the atmospheric circulation: passively, through statistical selection; and actively, through a physical model (as with spectrally nudged storylines). The most commonly used methods, together with their advantages and disadvantages compared to other strongly conditioned attribution methods, are summarized in Table 3 and are described in slightly more detail below. Of course, in any particular application more than one method can be used, as in the case of Ref. 23 discussed above.

A statistical downscaling technique termed Analogues was introduced by ref. 29. The key idea is to represent regional climate variables as a function of the large-scale atmospheric conditions (which is the rationale behind downscaling). For that, large-scale weather patterns for a given day are compared to high-resolution observation or reanalysis data, and time periods with the most similar circulation patterns (analogues) are selected. The observed weather at these times then serves as input to estimate the high-resolution climate state, assuming statistical stationarity. The technique can, for instance, be useful for statistical downscaling purposes or for paleoclimate reconstructions, but also for attribution of extreme events[30]. In the latter case, the difference between the analogue-estimated state and the actual state represents the thermodynamic component of climate change, relative to the reference period. For example, ref. 31 used the method to demonstrate that the cold European winter of 2010 was less cold than it would otherwise have been, because of anthropogenic warming.

Another statistical method of event attribution is termed Dynamical Adjustment. The method removes dynamical variations in a time series of a target variable, for instance by using empirical orthogonal functions, weather pattern clustering or linear regression, so that the anthropogenic climate change signal becomes more distinct[32,33]. The implicit assumption, as with storyline attribution, is that long-term dynamical variations are best regarded as internal variability. Rather than targeting a particular extreme event (as with Analogues), long-term trends are adjusted, although the decomposition can of course be examined for a particular event to provide an event attribution. Ref. 34 demonstrate the potential of dynamical adjustment as an attribution method for extreme events using the European cold spell and the Russian heat wave of 2010 as examples.

In regional climate modelling, a technique called Pseudo Global Warming (PGW) to study climate change effects on extreme events was presented by Ref. 35. It calculates climate change differences between global model simulations of e.g., present-day and pre-industrial climate or between future and present-day climate for important meteorological variables such as temperature, pressure, wind and humidity. These differences are then added to reanalysis data and constitute the PGW input data as modified boundary data for the regional climate model so that high-resolution simulations for the extreme event can be simulated for different climate states. The method is quite similar to spectrally nudged storylines, the difference is in its application being limited to regional studies and in not applying spectral nudging throughout the model domain. Although mainly used to study changes in climate, some studies have used PGW for attributing extremes to anthropogenic climate change, for instance, precipitation events over Asia[36] or typhoon-induced extreme precipitation[37].

Table 3 | Overview of strongly conditioned (storyline) event attribution methods

Strongly Conditioned (Storyline) Event Attribution Methods		
Attribution Methods	**How does it work?**	**Advantages/Disadvantages**
Statistical	The dynamic and thermodynamic components of a spatial timeseries (e.g., daily maps of surface temperature) are isolated statistically	No climate model simulations are needed The dynamic component is available for separate analysis, e.g., in terms of its long-term trends The thermodynamic component is estimated as a residual and may contain unidentified dynamic components A target variable must be chosen, restricting the method to univariate extremes Full 3-D fields are not available, limiting the use for impact studies
Analogues	The most similar circulation patterns (analogues) to a particular event are selected to represent the dynamical conditions	Observed changes in the frequency of the analogue states provide an estimate of the observed changes in the likelihood of the dynamical conditions conducive to the event, providing a bridge to probabilistic attribution Good analogues may not always be found
Dynamical Adjustment	Dynamically induced variations are statistically removed to isolate the anthropogenic climate change signal	The nature of the dynamical trend is not immediately interpretable
Modelled	A physical model is run in factual and counterfactual mode, with the circulation constrained in some way	Not restricted to the historical record so can consider unseen events The role of changing circulation is not directly estimated The model may have biases
Pseudo Global Warming	Differences between global simulations for various climates are added to reanalysis data to constrain the boundary conditions for regional extreme event simulations	Very similar in spirit to spectrally nudged storylines, but cannot be applied globally and suffers from the limitations of limited area models driven only from the boundary conditions
Short-term Forecasts	Historical extreme event forecasts with weather models are re-forecast under counterfactual conditions	Can use existing operational forecast systems Can represent any extreme that can be forecast Target events need to be identified Only useful for short-term events Interpretation of simulations is challenging because of statistical non-stationarity
Spectrally Nudged Storylines	Extreme events are simulated for different climates using similar large-scale circulation	Output is statistically homogeneous in space and time, so analysis is easy Events do not need to be predefined; different users can use different event definitions from the same simulations Set-up is easy to implement Small-scale events are not nudged and may differ between storylines The nudging needs to be adjusted

Another model-based event attribution method is to use short-term weather forecasts of the event, which are re-simulated under counter-factual conditions. Since the dynamical conditioning only occurs via the initial conditions, it weakens with forecast lead time because of the spread in the forecast ensembles through the butterfly effect. This leads to a temporal non-stationarity in the degree of conditioning as well as from spin-up of the climate response during the forecast, which complicates the statistical analysis[38]. Moreover, the dynamical conditioning is only effective for weather forecast timescales of a few days to a week, where the main anthropogenic effect comes from the counter-factual SSTs[38]. Hence the method has mainly been used for tropical cyclones[39], showing in particular that the rainfall was increased by anthropogenic climate change. Since the probability of the initial conditions is not assessed, it is still a conditional attribution. Another conditional attribution using a regional-model ensemble weather-hindcasting approach analysed the Colorado floods of September 2013, showing that anthropogenic drivers increased the magnitude of heavy precipitation[40].

Compared to the other model-based approaches, global spectrally nudged storylines have the key advantage of providing model fields that are both spatially and temporally statistically homogeneous, making the statistical analysis much simpler, at the cost of not necessarily being able to follow small-scale extreme events.

A new approach which is very similar in spirit to spectrally nudged storylines is to use a simple data assimilation system rather than spectral nudging to constrain the atmospheric state[41]. In this approach, the only atmospheric field assimilated is sea level pressure, which is combined with either factual or counter-factual SSTs. The method appears to be very effective for analysis of storms, and can be applied to historical storms in the distant past provided surface pressure observations are available. Thus, rather than asking how a recent extreme event would have been in the past, this method is able to ask how an extreme event from the distant past would be today. We do not include this method in Table 3 since there is not yet sufficient literature.

Impact-based studies applying spectrally nudged storylines

A new task for spectrally nudged storylines is to move forward from attribution of hazards to attribution of their impacts. So far, only a small number of such studies have been published. One of them is a storyline study on Hurricane Sandy's impact on New York City[42], which assessed how sea-level rise and changes in storm features affected coastal flooding impacts on critical infrastructure. To account for some degree of internal variability, the hurricane was altered in its landfall position, intensity and shape. It was found that even moderate increases in sea level and changes in storm tracks can affect flood impacts. A strength of this study is the simulation of the compound flooding effect of storm surge, high tide, sea level rise and extreme precipitation which caused the hurricane's impact on critical infrastructure. Through their specificity, storylines can provide a more advanced insight into the interaction of these drivers under past and future climate conditions.

Heat waves can lead to droughts, wildfires or crop failures. Extremely dangerous is the impact of heat on human mortality. This impact was assessed by ref. 43 for Germany. The aim was to predict the heat-related mortality for different future climate states based on storylines using advanced machine learning techniques. The storylines' factual and future climate data relies on observed extreme events and shows how their impact on mortality may change if these events would happen in a warmer world. This is one of the first studies to combine machine learning with spectrally

nudged storylines to attribute extreme event impacts. Neural networks are well suited and often superior to conventional statistical analysis in finding complex nonlinear relationships between extremes and variables such as mortality, provided that the underlying data basis is sufficiently large and of high quality. However, the machine learning model assumes that the climate-mortality relationship is not changing due to external factors in different climates, which may not be realistic in the far future.

In 2012, a large crop loss for soybeans, which even affected global food markets, occurred in the three largest soybean producing regions in the United States, Brazil, and Argentina due to compound hot and dry weather conditions. Ref. 44 examined the impact of climate change on soybean production for this extreme drought year using a statistical crop model combined with global storyline data. The study found that drought intensity did not change between the storylines, but higher temperatures and an intensified temperature-moisture interaction will lead to larger crop losses in the future. Applying such crop models to climate storylines may improve adaptation to climate change and communication with decision makers by identifying regions that are most vulnerable to anthropogenic climate change, e.g., where more irrigation or a change in crop type is needed.

Ref. 45 investigated near-surface ozone pollution levels in warmer climates, which would have health implications for humans and ecosystems. Storyline scenarios of air pollution were developed using a global atmospheric chemistry model to assess ozone pollution extremes in a warmer climate. The results point to two competing processes, which are dependent on the level of warming: vegetation and local photochemistry increase ozone extremes, while a concurrent moistening of the atmosphere leads to lower ozone concentrations. Such highly complex interrelating processes could well have been missed in a purely probabilistic attribution study, emphasizing the value of adding the storyline method in a combined attribution approach.

Outlook

Spectrally nudged storylines bring together the concepts of global climate downscaling (spectral nudging) and conditional attribution (storylines) to provide a methodology to predict surface climate from large-scale atmospheric circulation together with thermodynamic forcings, with the details filled in by the climate model. The methodology is easy to implement and easy to interpret, whilst respecting the complexity of a local situation, and thus exemplifies the key principles of "Small is Beautiful"[46]. We conclude this piece by reflecting on how spectrally nudged storylines can contribute to the changing face of climate science.

Impact attribution

There is a rapidly growing demand for attribution of climate impacts, yet this inevitably involves multiple causal factors, not just climate change. It is highly misleading if disasters are attributed solely to climate change, even if climate change increased their likelihood. In order to go from hazards to impacts for particular events, specific causation is needed: general causation is not sufficient[47]. Spectrally nudged storylines have the potential to fill this gap, as the few existing studies already show. What is needed is the inclusion of impact models with realistic intervention points, so that counterfactuals in the decision space can be combined with climate counterfactuals. Digital twins[48] offer promise in this respect.

Unseen events

Risk management requires examining things that might have happened (so-called 'downward counterfactuals') rather than just those that did happen. There is rapidly growing work in this space, either mining large ensemble simulations[49], or boosting ensemble members to create extremes that are more extreme than those observed[50]. This is very much in the spirit of 'tales of future weather'[51], but for the present. Such unseen events could be used to spectrally nudge higher resolution climate models and propagate the events through to impacts.

Dynamical aspects of climate change

A long-recognized limitation of the storyline approach to event attribution is its inability to account for possible changes in atmospheric circulation. This has been justified by the importance of quantifying the robust aspects of climate change, given the ambiguity of predicted circulation changes from climate models at the regional scale. However, circulation changes are beginning to emerge in the ever-lengthening observed record, and very often, they lie outside the range of changes predicted by the climate models, even after accounting for internal variability[52]. This raises the question of whether storylines of circulation change based on observations might be more useful than those based on the climate models themselves[53]. Spectral nudging using these observed circulation trends could be used to expand the range of explanatory factors considered in event storylines.

Bridging between specific and general causation

Both specific (storyline) and general (probabilistic) attribution have their purposes, and their strengths and weaknesses. Given the widespread prevalence of probabilistic event attribution and its planned operationalization, it is important to be able to connect the two approaches, and connect them both to attribution of changes in the statistics of extreme events, as reflected in aggregations over many events (and as discussed, e.g., in IPCC Assessment Reports). Because global spectrally nudged storylines are not event-specific but include all events worldwide during the simulation period, collections of events can be analysed, as with the attribution of a single hurricane season by aggregating over all forecasted hurricanes using the short-term forecast method[54]. This would also help connect attribution of historical events to long-term trends and future risk.

Global km-scale modelling

There is a growing push for the use of km-scale atmospheric models in order to explicitly model atmospheric convection, which is important for extreme events such as heavy precipitation[55]. Such models are very computationally expensive to run, however, which effectively precludes their use in probabilistic attribution. Any short simulation is necessarily conditional on the large-scale conditions. As already mentioned, spectral nudging provides an interpretable conditionality so that the short simulations can be more effectively compared against observations, and used for event attribution.

Artificial Intelligence (AI)

AI could further enhance the potential of climate storylines. In their recent study, Ref. 56 assess an AI-based weather and climate model in simulating extreme heat waves. They show that the model can realistically reproduce such events in different climate states. However, the study also points to a limiting factor. In comparison to physics-based models the AI-model tends to underestimate future warming. As a reason for this the authors suggest the absence of land-atmosphere feedbacks in the AI-based model. Perturbing AI-based models (analogously to how spectrally nudged AGCMs are perturbed with SSTs) has been shown to produce physically realistic responses in some AI-based weather models[57]. For application to extreme event attribution, AI is very well suited not just for detection and attribution of extreme events, but also for the detection of nonlinear relationships and drivers of extremes[58]. New AI attribution methods are currently explored in the EU-funded projects Climate Intelligence (CLINT, https://climateintelligence.eu/) and eXtreme events: Artificial Intelligence for Detection and Attribution (XAIDA, https://xaida.eu/) which already show promising results into the direction of combining AI and storyline attribution to result in a common attribution framework.

Received: 17 June 2025; Accepted: 31 July 2025;
Published online: 18 August 2025

References

1. National Academies of Sciences, Engineering & Medicine. *Attribution of Extreme Weather Events in the Context of Climate Change* (The National Academies Press, 2016). https://doi.org/10.17226/21852.
2. Hasselmann, K. Multi-pattern fingerprint method for detection and attribution of climate change. *Clim. Dyn.* **13**, 601–611 (1997).
3. Palmer, T. N. & Räisänen, J. Quantifying the risk of extreme seasonal precipitation events in a changing climate. *Nature* **415**, 512–514 (2002).
4. Lindley, D. V. Understanding Uncertainty, Revised Edition | Wiley. *Wiley.com* https://www.wiley.com/en-gb/Understanding+Uncertainty%2C+Revised+Edition-p-9781118650127 (2014).
5. Stott, P. A. et al. Attribution of extreme weather and climate-related events. *WIREs Clim. Change* **7**, 23–41 (2016).
6. Bueno de Mesquita, E. & Fowler, A. Thinking Clearly with Data | Princeton University Press. https://press.princeton.edu/books/hardcover/9780691214368/thinking-clearly-with-data (2021).
7. Shepherd, T. G. Atmospheric circulation as a source of uncertainty in climate change projections. *Nat. Geosci.* **7**, 703–708 (2014).
8. Trenberth, K. E., Fasullo, J. T. & Shepherd, T. G. Attribution of climate extreme events. *Nat. Clim. Change* **5**, 725–730 (2015).
9. Shepherd, T. G. A common framework for approaches to extreme event attribution. *Curr. Clim. Change Rep.* **2**, 28–38 (2016).
10. Lloyd, E. A. & Oreskes, N. Climate change attribution: when is it appropriate to accept new methods?. *Earths Future* **6**, 311–325 (2018).
11. Lorenz, E. N. *The Essence of Chaos* (University of Washington Press, 1993). https://doi.org/10.4324/9780203214589.
12. von Storch, H., Langenberg, H. & Feser, F. A spectral nudging technique for dynamical downscaling purposes. *Mon. Weather Rev.* **128**, 3664–3673 (2000).
13. Waldron, K. M., Paegle, J. & Horel, J. D. Sensitivity of a spectrally filtered and nudged limited-area model to outer model options. *Mon. Weather Rev.* **124**, 529–547 (1996).
14. Weisse, R. & Feser, F. Evaluation of a method to reduce uncertainty in wind hindcasts performed with regional atmosphere models. *Coast Eng.* **48**, 211–225 (2003).
15. von Storch, H. et al. Regional reanalysis without local data: Exploiting the downscaling paradigm. *J. Geophys. Res. Atmos.* **122**, 8631–8649 (2017).
16. Schubert-Frisius, M., Feser, F., von Storch, H. & Rast, S. Optimal spectral nudging for global dynamic downscaling. *Mon. Weather Rev.* **145**, 909–927 (2017).
17. Jeuken, A. B. M., Siegmund, P. C., Heijboer, L. C., Feichter, J. & Bengtsson, L. On the potential of assimilating meteorological analyses in a global climate model for the purpose of model validation. *J. Geophys. Res.* **101**, 16939–19950 (1996).
18. van Garderen, L., Feser, F. & Shepherd, T. G. A methodology for attributing the role of climate change in extreme events: a global spectrally nudged storyline. *Nat. Hazards Earth Syst. Sci.* **21**, 171–186 (2021).
19. Kooperman, G. J. et al. Constraining the influence of natural variability to improve estimates of global aerosol indirect effects in a nudged version of the Community Atmosphere Model 5. *J. Geophys. Res. Atmos.* **117**, D23204 (2012).
20. Shepherd, T. G. et al. Reconciliation of halogen-induced ozone loss with the total-column ozone record. *Nat. Geosci.* **7**, 443–449 (2014).
21. Wehrli, K., Hauser, M. & Seneviratne, S. I. Storylines of the 2018 Northern Hemisphere heatwave at pre-industrial and higher global warming levels. *Earth Syst. Dyn.* **11**, 855–873 (2020).
22. Sánchez-Benítez, A., Goessling, H., Pithan, F., Semmler, T. & Jung, T. The July 2019 European Heat Wave in a warmer climate: storyline scenarios with a coupled model using spectral nudging. *J. Clim.* **35**, 2373–2390 (2022).
23. Feser, F., van Garderen, L. & Hansen, F. The Summer Heatwave 2022 over Western Europe: an attribution to anthropogenic climate change. *Bull. Am. Meteorol. Soc.* **105**, E2175–E2179 (2024).
24. van Garderen, L. & Mindlin, J. A storyline attribution of the 2011/2012 drought in Southeastern South America. *Weather* **77**, 212–218 (2022).
25. Athanase, M., Sánchez-Benítez, A., Monfort, E., Jung, T. & Goessling, H. F. How climate change intensified storm Boris' extreme rainfall, revealed by near-real-time storylines. *Commun. Earth Environ.* **5**, 1–5 (2024).
26. John, A. et al. Global Storyline Simulations at the Kilometre-scale. Preprint at https://doi.org/10.22541/essoar.173160166.64258929/v1 (2024).
27. Klimiuk, T. et al. The European summer heatwave of 2019—a regional storyline perspective. *Earth Syst. Dyn.* **16**, 239–255 (2025).
28. Jones, A. D. et al. Continental United States climate projections based on thermodynamic modification of historical weather. *Sci. Data* **10**, 664 (2023).
29. Zorita, E. & von Storch, H. The analog method as a simple statistical downscaling technique: comparison with more complicated methods. *J. Clim.* **12**, 2474–2489 (1999).
30. Jézéquel, A., Yiou, P. & Radanovics, S. Role of circulation in European heatwaves using flow analogues. *Clim. Dyn.* **50**, 1145–1159 (2018).
31. Cattiaux, J. et al. Winter 2010 in Europe: A cold extreme in a warming climate. *Geophys. Res. Lett.* **37**, L20704 (2010).
32. Smoliak, B. V., Wallace, J. M., Lin, P. & Fu, Q. Dynamical adjustment of the northern hemisphere surface air temperature field: methodology and application to observations. *J. Clim.* **28**, 1613–1629 (2015).
33. Lehner, F., Deser, C. & Terray, L. Toward a new estimate of "time of emergence" of anthropogenic warming: insights from dynamical adjustment and a large initial-condition model ensemble. *J. Clim.* **30**, 7739–7756 (2017).
34. Terray, L. A dynamical adjustment perspective on extreme event attribution. *Weather Clim. Dyn.* **2**, 971–989 (2021).
35. Schär, C., Frei, C., Lüthi, D. & Davies, H. C. Surrogate climate-change scenarios for regional climate models. *Geophys. Res. Lett.* **23**, 669–672 (1996).
36. Kwon, D., Min, S.-K., Lee, M., Seo, G.-Y. & Son, S.-W. Attribution of 2022 August heavy precipitation event in South Korea using high-resolution pseudo global warming simulations: sensitivity to vertical temperature changes. *Geophys. Res. Lett.* **52**, e2024GL112392 (2025).
37. Tanaka, T., Kawase, H., Imada, Y., Kawai, Y. & Watanabe, S. Risk-based versus storyline approaches for global warming impact assessment on basin-averaged extreme rainfall: a case study for Typhoon Hagibis in eastern Japan. *Environ. Res. Lett.* **18**, 054010 (2023).
38. Leach, N. J., Weisheimer, A., Allen, M. R. & Palmer, T. Forecast-based attribution of a winter heatwave within the limit of predictability. *Proc. Natl. Acad. Sci. USA* **118**, e2112087118 (2021).
39. Reed, K. A., Stansfield, A. M., Wehner, M. F. & Zarzycki, C. M. Forecasted attribution of the human influence on Hurricane Florence. *Sci. Adv.* **6**, eaaw9253 (2020).
40. Pall, P. et al. Diagnosing conditional anthropogenic contributions to heavy Colorado rainfall in September 2013. *Weather Clim. Extrem.* **17**, 1–6 (2017).
41. Hawkins, E., Compo, G. P. & Sardeshmukh, P. D. ESD Ideas: translating historical extreme weather events into a warmer world. *Earth Syst. Dyn.* **14**, 1081–1084 (2023).
42. Goulart, H. M. D. et al. Compound flood impacts from Hurricane Sandy on New York City in climate-driven storylines. *Nat. Hazards Earth Syst. Sci.* **24**, 29–45 (2024).
43. Schachtschneider, R., Saynisch-Wagner, J., Sánchez-Benítez, A. & Thomas, M. Neural network based estimates of the climate impact on mortality in Germany: application to storyline climate simulations. *Sci. Rep.* **14**, 26074 (2024).

44. Hamed, R. et al. One-third of the global soybean production failure in 2012 is attributable to climate change. *Commun. Earth Environ.* **6**, 1–9 (2025).
45. Emmerichs, T. et al. Widespread reduction of ozone extremes in storylines of future climate. *Npj Clean Air* **1**, 19 (2025).
46. Rodrigues, R. R. & Shepherd, T. G. Small is beautiful: climate-change science as if people mattered. *PNAS Nexus* **1**, pgac009 (2022).
47. Perkins-Kirkpatrick, S. E. et al. On the attribution of the impacts of extreme weather events to anthropogenic climate change. *Environ. Res. Lett.* **17**, 024009 (2022).
48. Hazeleger, W. et al. Digital twins of the Earth with and for humans. *Commun. Earth Environ.* **5**, 463 (2024).
49. Thompson, V. et al. High risk of unprecedented UK rainfall in the current climate. *Nat. Commun.* **8**, 107 (2017).
50. Fischer, E. M. et al. Storylines for unprecedented heatwaves based on ensemble boosting. *Nat. Commun.* **14**, 4643 (2023).
51. Hazeleger, W. et al. Tales of future weather. *Nat. Clim. Change* **5**, 107–113 (2015).
52. Shaw, T. A. et al. Regional climate change: consensus, discrepancies, and ways forward. *Front. Clim*. **6**, 1391634 (2024).
53. Mindlin, J., Shepherd, T. G., Osman, M., Vera, C. S. & Kretschmer, M. Explaining and predicting the Southern Hemisphere eddy-driven jet. *Proc. Natl. Acad. Sci. USA* **122**, e2500697122 (2025).
54. Reed, K. A., Wehner, M. F. & Zarzycki, C. M. Attribution of 2020 hurricane season extreme rainfall to human-induced climate change. *Nat. Commun.* **13**, 1905 (2022).
55. Fowler, H. J. et al. Anthropogenic intensification of short-duration rainfall extremes. *Nat. Rev. Earth Environ.* **2**, 107–122 (2021).
56. Duan, S., Zhang, J., Bonfils, C. & Pallotta, G. Testing NeuralGCM's capability to simulate future heatwaves based on the 2021 Pacific Northwest heatwave event. *Npj Clim. Atmos. Sci.* **8**, 251 (2025).
57. Hakim, G. J. & Masanam, S. Dynamical tests of a deep learning weather prediction model. *Artif. Intell. Earth Syst*. **3**, https://doi.org/10.1175/AIES-D-23-0090.1 (2024).
58. Spuler, F. R., Kretschmer, M., Balmaseda, M. A., Kovalchuk, Y. & Shepherd, T. G. Learning predictable and informative dynamical drivers of extreme precipitation using variational autoencoders. *Weather Clim. Dyn.* in press (2025).
59. Lloyd, E. A. & Shepherd, T. G. Foundations of attribution in climate-change science. *Environ. Res. Clim.* **2**, 035014 (2023).
60. Intergovernmental Panel On Climate Change (IPCC). *Climate Change 2021 – The Physical Science Basis: Working Group I Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. (Cambridge University Press, 2023). https://doi.org/10.1017/9781009157896.
61. Otto, F. E. L., Massey, N., van Oldenborgh, G. J., Jones, R. G. & Allen, M. R. Reconciling two approaches to attribution of the 2010 Russian heat wave. *Geophys. Res. Lett*. **39**, L04702 (2012).

Acknowledgements

This article contributes to the European Union H2020 Project "CLIMATE INTELLIGENCE Extreme events detection, attribution and adaptation design using machine learning (CLINT)", Ref: 101003876-CLINT, to the BMFTR-project ClimXtreme-A5 (01 LP 2322 B), the BMFTR-project WAKOS-2 (01LR2003A1) and to the European Union H2020 XAIDA Project, grant no. 101003469. F.F. would like to thank H. von Storch for constructive discussions on the topic.

Author contributions

F.F. and T.G.S. wrote the article.

Competing interests

The authors declare no competing interests.

Additional information

Supplementary information The online version contains supplementary material available at https://doi.org/10.1038/s43247-025-02659-6.

Correspondence and requests for materials should be addressed to Frauke Feser.

Peer review information *Communications Earth & Environment* thanks and the other, anonymous, reviewer(s) for their contribution to the peer review of this work. Primary Handling Editor: Aliénor Lavergne. [A peer review file is available].

Reprints and permissions information is available at http://www.nature.com/reprints

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Open Access This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit http://creativecommons.org/licenses/by/4.0/.

© The Author(s) 2025, corrected publication 2025