

1 **Framing the question of attribution of extreme weather events**

2 **Friederike E. L. Otto<sup>1\*</sup>, Geert Jan van Oldenborgh<sup>2</sup>, Jonathan Eden<sup>2</sup>, Peter A. Stott<sup>3</sup>, David J. Karoly<sup>4</sup>,**  
3 **and Myles R. Allen<sup>1,5</sup>**

4 *\*friederike.otto@ouce.ox.ac.uk*

5 *1 Environmental Change Institute, University of Oxford, Oxford, UK.*

6 *2 Royal Netherlands Meteorological Institute (KNMI), P.O. Box 201, 3730 AE De Bilt, The Netherlands.*

7 *3 Climate Monitoring and Attribution □ Met Office Hadley Centre, Fitzroy Road, Exeter. EX1 3PB, UK.*

8 *4 ARC Centre of Excellence for Climate System Science, School of Earth Sciences, University of Melbourne,*  
9 *Melbourne, Australia.*

10 *3 Atmospheric, Oceanic and Planetary Physics, Department of Physics, University of Oxford, Oxford, UK.*

11 **Understanding how the overall risks of extreme events are changing in a warming world**  
12 **requires both a thermodynamic perspective and an understanding of changes in the**  
13 **atmospheric circulation.**

14 The extent to which human-induced climate change has played a role is a question routinely asked  
15 whenever an extreme weather or climate-related event occurs. Increasingly scientists are able to  
16 give robust quantitative answers to this question. In 2012, the Bulletin of the American  
17 Meteorological Society published the first annual special issue looking at how climate change may  
18 have affected the strength and likelihood of individual extreme events that took place during the  
19 previous year. This first issue contained just six papers [1]. Since then the science of event  
20 attribution has developed rapidly with an increasing number of research groups applying a wider  
21 range of methodologies (e.g., [2]), and the US National Academy of Sciences has just completed a  
22 report into the issue, concluding “in many cases, it is now often possible to make and defend  
23 quantitative statements about the extent to which human-induced climate change (or another

24 causal factor, such as a specific mode of natural variability) has influenced either the magnitude or  
25 the probability of occurrence of specific types of events or event classes.”[3]

26 While the thermodynamic consequences of a warming world, namely an increased likelihood of  
27 more heat and high-precipitation extremes, are predictable (e.g. [4]) on average, in any specific  
28 location or circumstances, thermodynamic influences may be either amplified or counteracted by  
29 anthropogenically induced changes in circulation (e.g [5]; [6]; [7]) and or other local forcings [8]. As  
30 far as impacts are concerned, the mechanism whereby human influence on global climate is  
31 manifest in a particular weather event is immaterial, so to understand how the risks of extreme  
32 events are changing requires both a thermodynamic and a dynamic perspective. The emerging  
33 science of probabilistic event attribution provides tools needed to assess such risks at the spatial  
34 scales people care about.

### 35 **Multiple Approaches**

36 Overall, there is great strength in using different approaches to assess the role of anthropogenic  
37 climate change in extreme weather events as it allows estimates of the uncertainty in attribution  
38 statements beyond sampling uncertainty [9] thereby increasing confidence in the result. However,  
39 differences in how the attribution question is framed can lead to apparently contradictory answers  
40 to attribution questions that provide a challenge in communication, often reinforced by high media  
41 attention. An example where seemingly contradictory results are in fact complementary is provided  
42 by the studies of the Russian heat wave in 2010, where the magnitude of the event was mainly due  
43 to natural variability [10] while the likelihood of occurrence of an event of this magnitude had  
44 changed considerably due to anthropogenic drivers [11]. More subtle differences in analysing  
45 changes in the likelihood of occurrence can still lead to large discrepancies in results ([12]; [2]).

46 Other approaches to attribution have been suggested that allow improvements to our  
47 understanding of the event itself, but do not allow for an assessment of whether or how the risk of  
48 such an event has changed [13]. Such studies ask the question: conditional on the large-scale

49 circulation patterns, what was the role of anthropogenic climate change in this event (e.g. [7])? Such  
50 studies allow for assessing whether climate change altered known relationships between large-scale  
51 drivers and local events. One such example is discussed by King et al. [14] who investigated whether  
52 anthropogenic climate change affected the relationship between ENSO and extreme rainfall in  
53 South-East Australia. While not analysing the overall change in risk of an event occurring, isolating  
54 specific drivers can still be invaluable in improving understanding and in turn our ability to simulate  
55 extreme events. It is however important for such analyses to communicate their conditional nature.

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### 57 **Event Definition**

58 Apart from different ways of framing the attribution question, the second crucial step in extreme  
59 event attribution is the definition of the actual extreme event to analyse. Any definition involves an  
60 element of convention, but it is important for conventions to be consistent, transparent and above  
61 all relevant to the questions that stakeholders are asking. Every extreme weather event is ultimately  
62 caused by a unique combination of external drivers and internal chaotic variability. For those  
63 affected, however, whether they are asking if human-induced climate change is in any sense “to  
64 blame” or making planning decisions in disaster recovery, the defining characteristic is the harm  
65 caused, not the details of the meteorological precursors. Suppose anthropogenic changes in  
66 atmospheric circulation patterns are reducing the overall risk of storms in a particular region such  
67 that, despite the thermodynamic impact of warming contributing to the intensity of individual  
68 storms, overall risk of pluvial flooding is declining. It would be confusing, to blame anthropogenic  
69 climate change, even partially, for an observed pluvial flood if the actual impact is to make such  
70 flood events in that region less likely to occur. Likewise, in rebuilding decisions, what matters is the  
71 overall impact on risk, not the role of individual drivers in the specific event.

72 Hence in order to assess whether and to what extent the risk of an individual event occurring has  
73 been altered due to changes in the external drivers, e.g. an increase in greenhouse gases in the

74 atmosphere, the event needs to be defined in terms of a class of events that have similar or larger  
75 impacts. If only the observed event is studied, as suggested e.g. in Trenberth et al. [15], it will by  
76 definition never happen again [16]. Adopting too narrow a definition of the event as the basis for an  
77 attribution study may therefore bias attribution studies, irrespective of the role of anthropogenic  
78 climate change in overall risk. It is perfectly possible that removing an anthropogenic warming signal  
79 may reduce the magnitude of an event in a simulation in which all other factors, including the initial  
80 conditions and large-scale flow, are held constant, even if the net impact of anthropogenic climate  
81 change is to reduce the probability of occurrence of similar events, even with a very restrictive  
82 definition of similarity. Indeed, this result is more likely with the most extreme weather events,  
83 which occur, almost by definition, because both natural and anthropogenic drivers work together to  
84 generate the event in question. If any single driver is removed, the result may well be to weaken the  
85 event, regardless of the impact of that driver on overall risk.

86 Following early simplified scenario approaches [17], Trenberth et al. [15] suggest framing the  
87 attribution question: “given the atmospheric circulation that brought about the event, how did  
88 climate change alter its impacts?” They do not intend assessing the absolute probability for the  
89 event to occur, but only investigate the change in severity of the event given that it occurred.  
90 Although undoubtedly helpful in understanding the factors behind an event and guiding research  
91 into improving predictability, it must be understood that this way of framing the attribution question  
92 is intrinsically biased towards an outcome that may not be relevant to either the assignment of  
93 blame nor planning decisions in disaster recovery.

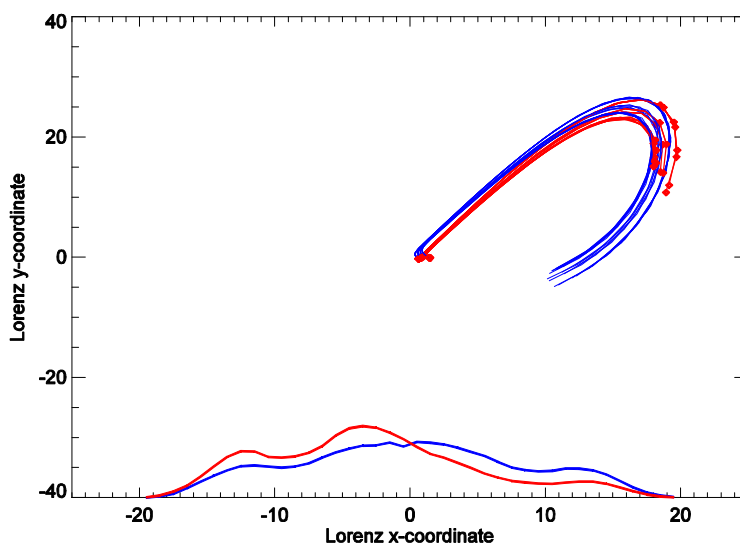
94 Figure 1 illustrates this using a simple chaotic system in which a constant external forcing is added to  
95 the Lorenz ‘63 model following Palmer (2003) [18]. The forcing acts in the X-Y plane, and its overall  
96 impact is to reduce the probability of a “high-X” extreme event<sup>1</sup>, as shown by the difference  
97 between the blue (no forcing) and red (forced) distributions on the X axis. If, however, the initial

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<sup>1</sup> Which part of the phase space is chosen as an extreme event is an arbitrary choice and the argument here is independent of that choice.

98 conditions are set to approximately one “Lorenz day” before a “high-X” event occurs, sufficiently  
 99 close that the large-scale flow is unchanged, the impact of removing the forcing (blue versus red  
 100 trajectories) is to reduce the magnitude of these individual “high-X” events. In this case, while it is  
 101 true that the external forcing is acting to increase the magnitude of an individual “high-X” event in  
 102 the immediate build-up to the event occurring, it would be misleading either to blame the forcing  
 103 for the occurrence of a “high-X” event when the forcing has actually acted to make such an event  
 104 less likely to occur, or to suggest we should be prepared for more such events as the forcing increases.  
 105 In a non-linear system, there will always be cases where the impact of the forcing conditioned on the  
 106 initial conditions can be in the opposite direction to the unconditioned impact of the forcing. Only a  
 107 probabilistic approach guards against over- or under-confidence in attribution of events to human  
 108 influence.

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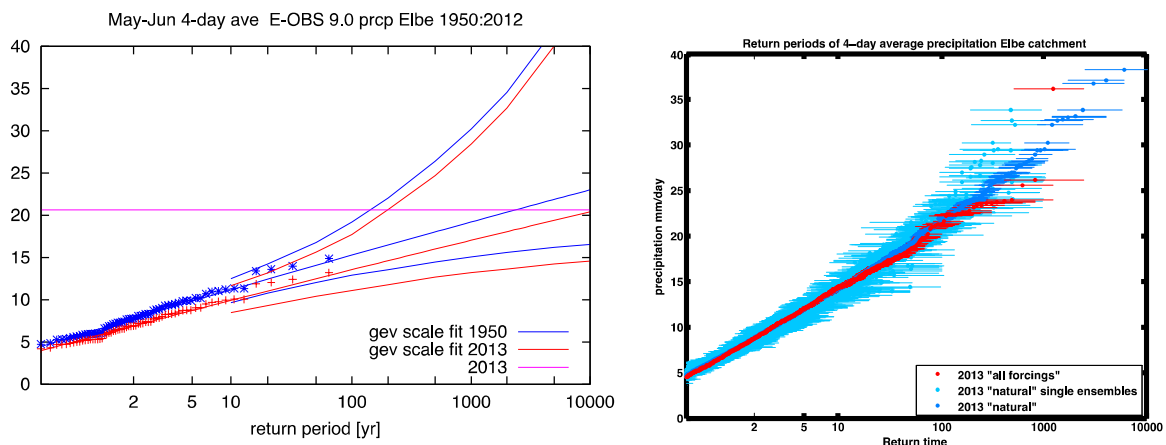
111 *system with added forcing. main figure) The Lorenz-attractor of a Lorenz system with a forcing symbolising the*  
 112 *current climate forcing in blue and , a weaker or natural forcing in red. The bottom of the figure shows the*  
 113 *distribution of x for both forcings for the most extreme events with the y-axis giving the occurrence probability*  
 114 *and the x-axis the strength of the event. The blue line is above the red line for all events with a positive x.*

### 115 Framing attribution/ real world examples

116 While the thermodynamic response of the climate system is often linear, the dynamic response can

117 be highly non-linear and may be in the opposite direction to the thermodynamic response. Hence

118 limiting attribution studies to the thermodynamic response alone as exemplified in [7, 15] does not  
 119 allow for an assessment of the actual risk of the event occurring as the large-scale dynamics can  
 120 counteract or enhance the thermodynamics. In practice the dynamic contribution is often of a  
 121 similar magnitude to the thermodynamic response (e.g. [5]; [6]). In the summer of 2013 heavy  
 122 flooding occurred in the Danube and Elbe basins in South East Germany resulting from extreme  
 123 precipitation, with some parts of the region receiving a months worth of precipitation in the 3 days  
 124 between the 30<sup>th</sup> May and 2<sup>nd</sup> June. In a warming climate we would expect from the fact that the  
 125 vapour capacity of the atmosphere increases with warming an increase in the likelihood of such rains  
 126 to occur of approximately 6%, as the temperature in this region and season has risen about 0.9 K. In  
 127 figure 2 we show the attribution analysis for the Elbe catchment as published in [5]. Analysing the  
 128 observation gives a return time of the event of roughly 200 years. An increase of 6% would render a  
 129 1 in 200 year event in a pre-industrial climate a 1 in 120 event in a warming climate. However, the  
 130 two independent methodologies used to analyse the overall change in risk show no change in the  
 131 likelihood of the event occurring. A 1 in 200 year event stays a 1 in 200 year event according to the  
 132 model analysis (with the 90% uncertainty ranging from 1 in 144 to 1 in 413) and becomes a more  
 133 than 1 in 100 in the statistical analysis (a result in the trend in the observations being negative). The  
 134 model results exclude a 7%/K increase. This implies there is an important role of the circulation.



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136 *Figure 2: Return time plots for the maximum four-day precipitation average during May–Jun in the E-OBS*  
 137 *dataset (a), and in HadRM3P (b) for the upper Elbe catchment. For the E-OBS dataset, red crosses indicate*  
 138 *years from 1950 to 2012 after correction for the fitted trend to the year 2013 and the red lines correspond to*  
 139 *the 95% confidence interval estimated with a non-parametric bootstrap. Blue crosses and lines represent the*

140 *same as the red but in the climate of 1950, and the horizontal purple line represents the observed value for*  
141 *May–Jun 2013. For the HadRM3P datasets, the red dots indicate May–Jun possible four-day maximum*  
142 *precipitation events in a large ensemble of HadRM3P simulations of the year 2013, while the light blue dots*  
143 *indicate possible May–Jun four-day maximum precipitation events in 25 different ensemble simulations of the*  
144 *year 2013 as it might have been without climate change. The blue dots represent the 25 natural ensembles*  
145 *aggregated together. The error-bars correspond to the 5%–95% confidence interval estimated with a non-*  
146 *parametric bootstrap.*

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148 Another example, where the dynamical component of any changes acts in the same way as the  
149 thermodynamic is given in [21]. The authors identify an increase in the occurrence probability of  
150 heavy winter precipitation in Southern England of 42% as the best guess (with a 0-160% range),  
151 corresponding to an increase in intensity of about 4%(+/- 1%). In addition to this the study explicitly  
152 analyses the change in the circulation, finding an increase in the zonal regime structure of the  
153 atmosphere.

154 In a study on the influence of anthropogenic greenhouse gas forcing on exceptional mean sea level  
155 pressure in southern Australia in the Winter season, [22] found that the risk of extremely high MSLP  
156 has increased by at least 70%. Such high sea level pressure precludes low pressure systems from  
157 coming in land to bring rainfall in Southern Australia, contributing to the decline in rainfall in that  
158 region. These findings corroborate earlier studies (e.g., [23]) and highlight again the importance of  
159 dynamical changes due to anthropogenic forcings in the overall risk assessment. A closely related  
160 example is the decline in winter rainfall in the southwest of Western Australia, mainly associated  
161 with circulation changes due to anthropogenic forcing [5], while the sea surface temperatures have  
162 increased and the thermodynamic response would suggest increased rainfall.

163

164 All three examples demonstrate that limiting the analysis to thermodynamic responses would give a  
165 misleading impression of the role of climate change. There are many more examples for a  
166 dominating role of the circulation (e.g., [5]; [6]; [8]) highlighting that a holistic assessment of the role  
167 of human-induced climate change can be rather complex. Robust attribution statements are only  
168 possible if the modelling approach is able to reliably reproduce the event in question as highlighted

169 by Trenberth et al. [15]. However, in numerous studies scientists have demonstrated that models  
170 are capturing the relevant processes in a reliable way and also hold off from conducting attribution  
171 studies if the models prove unreliable (e.g., [24]). This underlines that model evaluation and bias  
172 correction deserve close attention in attribution studies. In particular applying multiple methods to  
173 answer the same question allows for model dependent results to be identified and the uncertainty  
174 to be better quantified. Attribution assessments are more likely to be reliable where they are based  
175 on a solid foundation of physical understanding. Combining multiple methods and basing findings  
176 on physical principles is thus the recommended approach for all event attribution studies.

## 177 **Conclusion**

178 It is often stated that it is not possible to make an attribution statement about an individual weather  
179 or climate event [25]. To the extent that an attribution statement might refer to the particular  
180 unique circumstances of any event this still holds in the sense that any attribution statement would  
181 be uninformative. However, due to the considerable progress made in the last decade there is a  
182 informative alternative. Scientists can now provide reliable answers to the question of whether  
183 anthropogenic climate change has altered the probability of occurrence of classes of individual  
184 extreme weather events, which often is a relevant question. The emergence of a set of  
185 complementary approaches deepens our confidence in these results and paves the way to provide  
186 robust answers to questions from stakeholders and the public in the immediate aftermath of an  
187 extreme weather event. When communicating these results, it is important to clearly state the  
188 probabilistic framing of the attribution question, how the event is defined and the level of  
189 confidence in the findings based on physical understanding. If the attribution question is being asked  
190 to provide guidance from the present on what the future may hold, in general approaches  
191 accounting for the full change in probability provide useful answers. This does not imply that for  
192 specific stakeholder questions a conditional framing of the attribution question would not be  
193 desirable, e.g., given a regional typical convective situation will the magnitude of rainfall increase?  
194 However, from the perspective of a stakeholder seeking information to inform disaster risk

195 reduction strategies, it can be unhelpful to ask the question of how the probability has changed  
196 given the large-scale circumstances, as the risk crucially depends on these circumstances and their  
197 likelihood of occurring. As evidenced above, dynamical factors and thermodynamic aspects can  
198 interact in complex ways and there are many examples where the circulation is as important as the  
199 thermodynamics. Furthermore, if the event definition is too narrowly dependent on the exact  
200 atmospheric state and sea surface temperature patterns, the event may only occur if all factors are  
201 just right. This implies that all aspects of the external drivers, including human-induced climate  
202 change, are necessarily essential ingredients to reproduce the event.

203 In light of these facts it is important for every extreme event attribution study to clearly state the  
204 framing of the attribution question being asked. This should include whether conditional  
205 probabilities are being assessed or whether instead overall probabilities are being assessed,  
206 independent of sea surface temperatures, the atmospheric circulation state or other factors  
207 constraining the evolution of the particular event in question.

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