

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

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

24 specific mode of natural variability) has influenced either the magnitude or the probability of
25 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 [14] investigated whether anthropogenic climate change
52 affected the relationship between ENSO and extreme rainfall in South-East Australia. While not
53 analysing the overall change in risk of an event occurring, isolating specific drivers can still be
54 invaluable in improving understanding and in turn our ability to simulate extreme events. It is
55 however important for such analyses to communicate their conditional nature.

56

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, such as 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 in [15] for example, it will by definition
76 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, as shown by the difference between
97 the blue (no forcing) and red (forced) distributions on the X axis. If, however, the initial conditions
98 are set to approximately one “Lorenz day” before a “high-X” event occurs, sufficiently close that the
99 large-scale flow is unchanged, the impact of removing the forcing (blue versus red trajectories) is to

100 reduce the magnitude of these individual “high-X” events. In this case, while it is true that the
101 external forcing is acting to increase the magnitude of an individual “high-X” event in the immediate
102 build-up to the event occurring, it would be misleading either to blame the forcing for the
103 occurrence of a “high-X” event when the forcing has actually acted to make such an event less likely
104 to occur, or to suggest we should prepared for more such events as the forcing increases. In a non-
105 linear system, there will always be cases where the impact of the forcing conditioned on the initial
106 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.

109

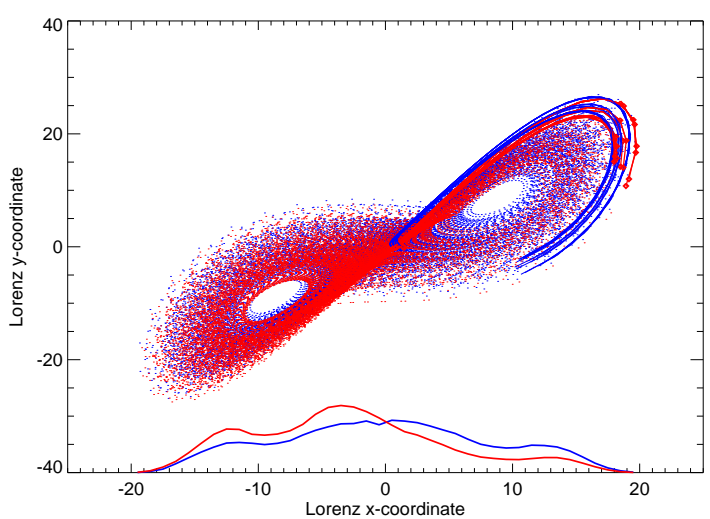


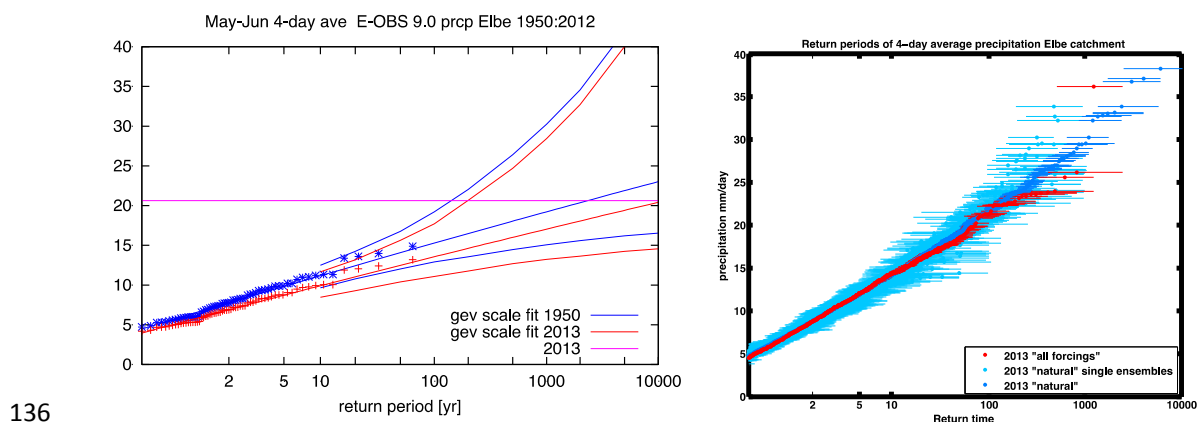
Figure 1: Simple chaotic Lorenz 63

110 system with added forcing. The main figure shows the Lorenz-attractor of a Lorenz system with a forcing
111 symbolising the current climate forcing in blue and, a weaker or natural forcing in red. The bottom of the figure
112 shows the distribution of x for both forcings for the most extreme events with the y-axis giving the occurrence
113 probability and the x-axis the strength of the event. The blue line is above the red line for all events with a
114 positive x.
115

116 **Framing attribution/ real world examples**

117 While the thermodynamic response of the climate system is often linear, the dynamic response can
118 be highly non-linear and may be in the opposite direction to the thermodynamic response. Hence
119 limiting attribution studies to the thermodynamic response alone as exemplified in [7, 15] does not
120 allow for an assessment of the actual risk of the event occurring as the large-scale dynamics can

121 counteract or enhance the thermodynamics. In practice the dynamic contribution is often of a
 122 similar magnitude to the thermodynamic response (e.g. [5]; [6]). In the summer of 2013 heavy
 123 flooding occurred in the Danube and Elbe basins in South East Germany resulting from extreme
 124 precipitation, with some parts of the region receiving a month's worth of precipitation in the 3 days
 125 between the 30th May and 2nd June. In a warming climate where the vapour capacity of the
 126 atmosphere increases with warming, we would expect the likelihood of such rains to occur to
 127 increase by approximately 6%, as the temperature in this region and season has risen about 0.9 K. In
 128 figure 2 we show the attribution analysis for the Elbe catchment as published in [5]. Analysis of the
 129 observation gives a return time of the event of roughly 200 years. An increase of 6% would render a
 130 1 in 200 year event in a pre-industrial climate a 1 in 120 year event in a warmer climate. However,
 131 the two independent methodologies used to analyse the overall change in risk show no change in
 132 the likelihood of the event occurring. A 1 in 200 year event stays a 1 in 200 year event according to
 133 the model analysis (with the 90% uncertainty ranging from 1 in 144 to 1 in 413) and becomes a more
 134 than 1 in 100 in the statistical analysis (a result in the trend in the observations being negative). The
 135 model results exclude a 7%/K increase. This implies there is an important role of the circulation.



137 *Figure 2: Return time plots for the maximum four-day precipitation average during May–Jun for the upper Elbe*
 138 *catchment. Panel (a) shows the return times calculated from the E-OBS dataset, and (b) from HadRM3P. For*
 139 *the E-OBS dataset, red crosses indicate years from 1950 to 2012 after correction for the fitted trend to the year*
 140 *2013 and the red lines correspond to the 95% confidence interval estimated with a non-parametric bootstrap.*
 141 *Blue crosses and lines represent the same as the red but in the climate of 1950, and the horizontal purple line*
 142 *represents the observed value for May–Jun 2013. For the HadRM3P datasets, the red dots indicate May–Jun*
 143 *possible four-day maximum precipitation events in a large ensemble of HadRM3P simulations of the year 2013,*
 144 *while the light blue dots indicate possible May–Jun four-day maximum precipitation events in 25 different*

145 *ensemble simulations of the year 2013 as it might have been without climate change. The blue dots represent*
146 *the 25 natural ensembles aggregated together. The error-bars correspond to the 5%–95% confidence interval*
147 *estimated with a non-parametric bootstrap.*

148

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

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

164

165 All three examples demonstrate that limiting the analysis to thermodynamic responses would give a
166 misleading impression of the role of climate change. There are many more examples for a
167 dominating role of the circulation (e.g., [5]; [6]; [8]) highlighting that a holistic assessment of the role
168 of human-induced climate change can be rather complex. Robust attribution statements are only
169 possible if the modelling approach is able to reliably reproduce the event in question as highlighted
170 by Trenberth et al. [15]. However, in numerous studies scientists have demonstrated that models

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

178 **Conclusion**

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

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

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

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