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Seminar: How do I lie with Statistics?

Climate Attribution Science

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13th January 2020

Contents

1 Introduction

Within the past few decades, extreme weather events have become more and more present in the daily news. In newspapers and on the internet we read about extreme wildfires, floods and hurricanes as well as new heat records almost every year [2, 3, 4]. This raises the question whether such weather extremes have in deed become more extreme and more frequent. A question which clearly is also subject to political debates. The mayor of Venice for instance speculates that Climate change is behind the extreme floods in summer 2019 [5].

Today an overwhelming scientific consensus holds that we are in fact experiencing a change in climate and that there is also a human-induced component to this global warming. However, in what ways and to what extend extreme weather events are influenced by climate change is still a question of ongoing research. The scientific field which deals with the attribution of extreme weather events to global warming is called climate attribution science. Since weather is a multicausal and complex phenomenon, linking individual, local weather patterns to global climate change is a highly complicated subject. Questions like 'was yesterday's extreme rain event caused by global warming?' therefore come along with the same problems as determining the cause of a single instance of cancer. In a multicausal world, it seems nearly impossible to pin down whether the BBQ event last summer was the critical influence to have actually 'caused' a given form of cancer.

The objective of this report will be to give an overview of how well climate attribution science does on answering the following questions: Did anthropogenic climate change make an extreme weather event more likely? And did it make it more severe? Furthermore, it will be demonstrated from a simple Toy model simulation how it is possible to compare an extreme precipitation event in a world *with* global warming to a corresponding event in a world *without*. Thereby, we will see how understanding the underlying physics of weather extremes combined with computational simulation even allows to tackle questions such as: To what extend was the storm flood of Hurricane Katrina in 2005 caused by human-induced global warming? Clearly, the answer to such questions is not only of scientific interest but also has great importance for politics, economics and people.

2 What is Climate Attribution Science?

Climate attribution science as such is a relatively new field of science. The first example of attribution studies in the context of weather extremes and climate change were published in 2004. At this time, the summer of 2003 had probably been the hottest in Europe since at least 1500 A.D. and came along with unusually large numbers of heat-related death reports in Italy, Germany and France [1]. In their Nature article, the climate scientists Stott, Stone and Allen therefore analysed the human contribution to the European heat wave in 2003. In general, one finds that the attribution of weather extremes to climate change is based on the interplay of the following 3 keystones:

1. Physics and mechanisms behind weather extremes
2. Historical observations
3. Computer simulations

In the following, let us briefly consider some basic aspects of these three groundings of extreme event attribution.

2.1 Physics and mechanisms behind weather extremes

In order to understand the central role of sound physics in weather processes, let us first make a clear distinction between climate on one side and weather on the other.[1] When describing or predicting changes in climate, one can rely well-understood physical laws, for example the laws thermodynamics. These allow to stably predict the evolution of key quantities such as the global mean temperature, the amount of water vapour in the atmosphere or the sea level. From the inferred evolution one may then deduce robust thermodynamical trends based on simple physics causation, much like: Higher surface temperatures lead to more evaporation, which will on average cause more drought where water evaporates and more precipitation on the other end of the water cycle (see Fig. 1). Furthermore, warmer atmosphere can generally hold more moisture so that the rise in atmospheric temperature will on average bring heavier rain and heavier snow fall.

On the contrary, weather can be thought of the noisy dynamics on top of long-term trends and is hence very hard to predict. More technically speaking, weather is *chaotic* which is also the reason why meteorologists may already in October predict that a rough winter is coming but are incapable of giving a precise weather forecast for more than just a few days ahead.

[1] The clear distinction used here is rather semantics. Practically, the definitions of what is weather and what is climate are of course more strongly intertwined.

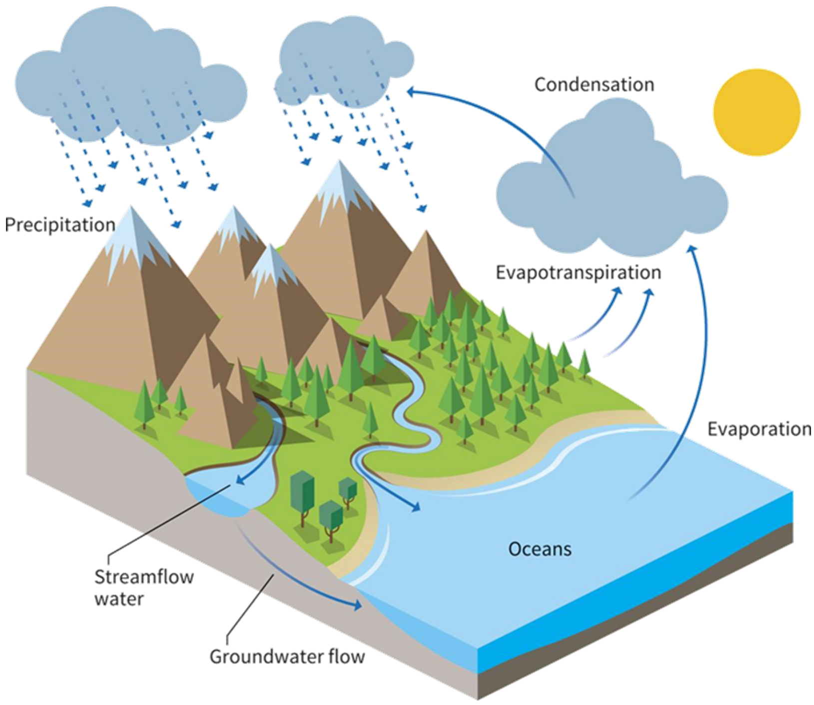

Figure 1: Water cycle from evaporation to precipitation [6].

2.2 Historical observations and Computer simulations

Attribution science further relies on the interplay of historical observations and simulations. Like in every other field of science, observations and model building have to complement each other. From historical records one may infer how the frequencies and the characteristics of certain extreme events have changed over the years. However, a crucial problem related to observations is that extreme events are rare by definition. At a given location there might hence be just very few records of previous events to actually study both characteristics and frequencies.

In a complementary manner, computer simulations are used to predict how the phenomenology of extreme weather events may evolve in a future of ongoing climate change. Computer simulations can even estimate how certain weather extremes today would look given a different past. These so-called *counterfactual* scenarios (e.g. 'How would weather extremes look today if the industrial revolution had never taken place?') will play an essential role when determining the influence of certain climate factors on weather extremes. Moreover, the need for computer simulations is evident since climate experiments in a global sense are simply not possible. The possibilities of counterfactual simulations and how they are applied in climate attribution science will be illustrated in chapter 4.

3 A complexity approach to weather extremes

The dominating scientific approach in the 20^{th} century was based on the philosophy of *reductionism* that the complex world is nothing but the sum of its parts. The complexity approach however proposes that the complex world is actually more than just the sum of its parts. It grounds on the idea that complex systems which consist of many interacting units, e.g. an ant colony, give rise to *emergent* behaviour which cannot be understood by studying a single unit in isolation [7]. Weather can therefore also be seen as complex phenomenon. To give a more illustrative idea of how complexity arises in a system, let us below consider a Toy model of a sand pile. We will later on see how this simplistic sand pile model qualitatively behaves very much analogue to a model of precipitation in the atmosphere.

3.1 The sand pile metaphor

Even tough a single sand pile seems like a very simple model to start with, it already displays some very interesting behaviour. Thus, let us consider a simulated one-dimensional sand pile which is built on a table of finite size L and constrained to the left by a wall (see Fig. 2). We define the local slope z_i at a given site i to be the height difference of the pile at this site compared to the next one at $i+1$. After initializing our model by assigning critical slopes $z_{i,crit} \in 1, 2$ to each site, the sand pile is built executing the following algorithm:

1. Add a sand grain to the first site ($i = 0$).
2. If at any site i the local slope z_i exceeds the assigned critical slope $z_{i,crit}$, i.e. the sand pile becomes to steep, then:
   - Let one grain of site i topple down to the next site $i+1$ (Relaxation).
   - Assign a new critical slope to site i chosen randomly according to:

$$z_{i,crit} = \begin{cases} 1 & \text{with probability } p \\ 2 & \text{with probability } 1-p. \end{cases}$$

3. Repeat.

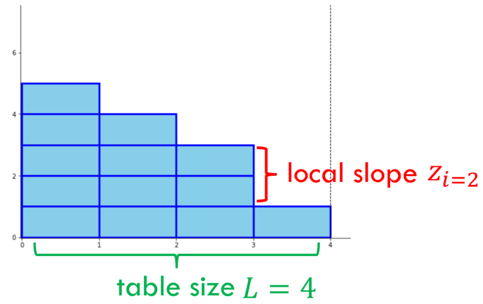

Figure 2: One-dimensional sand pile model on a table of finite size.

An example of how such a sand pile is built in the case of $L = 4$ and $p = 1$ can be found in Fig. 3. Note that for $p = 1$ all critical slopes are equal to 1. Next, let us define the avalanche size s as the total number of relaxations induced by adding a single grain to the pile. We then see that after the sand pile has reached the configuration in Fig. 3.8, it behaves trivially. Every further grain which is added to the system topples down the entire pile and thereby produces an avalanche of size 4. When the grain then relaxes from the last site, it figuratively speaking falls off the table and thereby leaves the system.

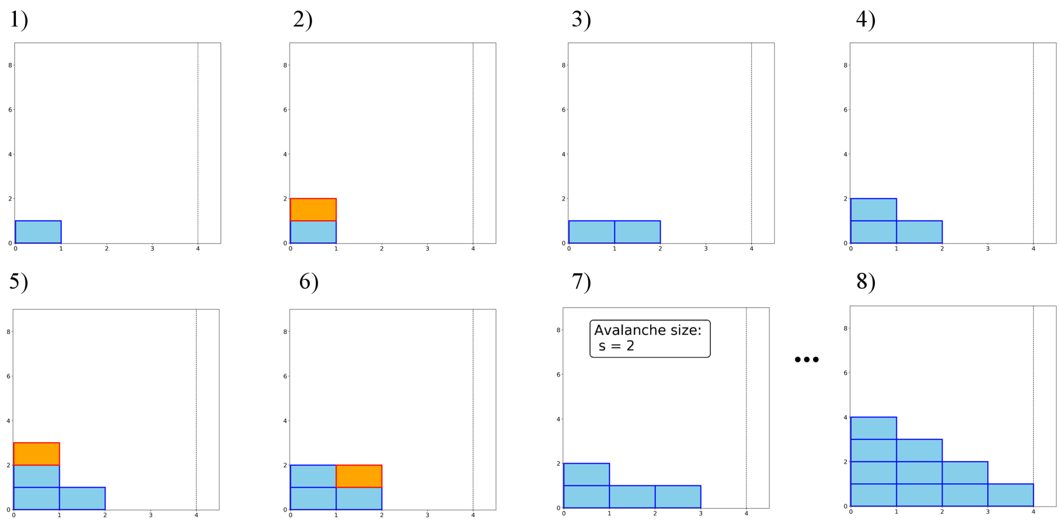

Figure 3: Building up a simple one-dimensional sand pile model: At each time step, we add a grain at the first site and relax a grain if the critical slope is exceeded (indicated in orange). In this trivial case of $p = 1$, all critical slopes are set to 1.

The sand pile model becomes non-trivial if the assignment of critical slopes $z_{i,crit}$ is randomised by setting $p = 0.5$. For this case, sand piles of different system sizes were built. After reaching the steady state of the pile, i.e. the point at which the first grain topples out the system, 10^5 further grains were added and all occurring avalanche sizes were plotted in a histogram using logarithmic bin widths (see Fig. 4a).[2]

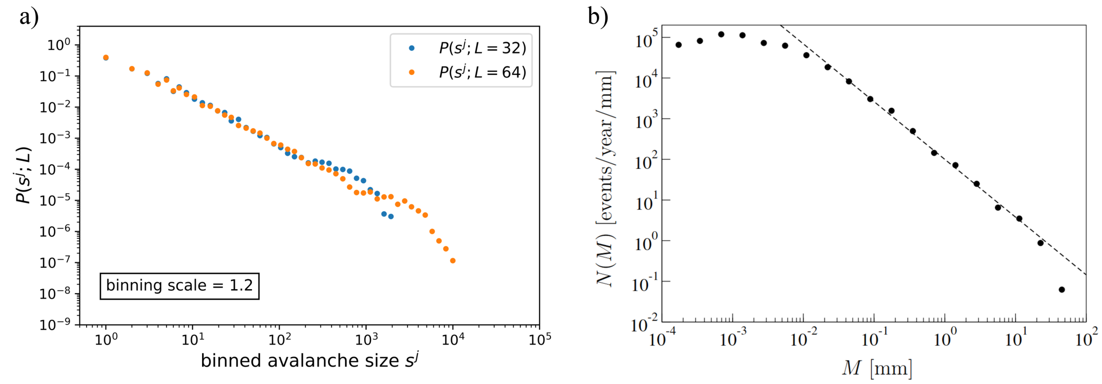

Figure 4: a) Avalanche size probability distribution for sand piles of size $L = 32$ and $L = 64$: The avalanche sizes are distributed according to a power law. In principle avalanches of all sizes appear. Only due to the finite number of grains we experience a finite size cut-off. b) Number of rainfalls plotted vs. total amount of rain fallen in mm based on data from METEK covering the period 1.1.1999 to 1.7.1999 at the Baltic coast Zingst, Germany.

The two event size distributions of real-world precipitation data and the avalanches in our sand pile Toy model in Fig. 4 both trace out very similar power law distributions, thus showing that both systems show qualitatively analogous behaviour. Furthermore, such power law distributions can be found in all different fields of nature and our everyday lives, including earthquake magnitudes, wealth distributions, networks like the WWW and many more [7]. However, the special feature of the sand pile model is however the following: From simple rules the sand pile organises itself into a state of criticality. That means a state in which smallest inputs (a single grain) produce avalanches of all orders of magnitude. This behaviour is called *self-organised criticality* and provides an interesting mechanism and possible explanation regarding the question why these power law distribution in fact appear all around us. The bottom-line of self-organised criticality is that for many of these systems, extreme events are unlikely but not unusual. They need no special 'cause' or initialisation but are rather inherently part of the system. So, does that mean that weather extremes are all just due to natural variability? In the next chapter, we will take a look at different couterfactual scenarios to see how global warming and human influences are still part of the equation.

[2] The log-binning scale was chosen to be 1.2 in all cases.

4 From the sand pile to real-world attribution

Sticking to the rainfall analogy, let us metaphorically think of the sand pile as the Earth's atmosphere or a set of clouds. In these cloud more and more moisture builds up until the clouds relax in an avalanche-like precipitation process. In this picture, a possible way to include a global warming effect is to increase the evaporation. In terms of the sand pile model, this would for example correspond to now adding 4 grains at each time step instead of 1. Figure 5 shows how the avalanche size probability distribution changes under such a forcing. Due to the analogy we would expect an increase in evaporation to have a very similar effect on rainfall occurrences. Figure 5 shows that due to the increased 'evaporation' extreme events of the same size have become roughly a factor of 10 more likely. On the other hand, if we ask how an event has changed in magnitude, that occurs which a fixed probability (e.g. 'How strong is an event which is expected to appear once every 5 years?'), we find its strength has increased also by a factor of 5-10. This means that such a computer simulation can provide us with a probability for an extreme weather event in a world with human-caused climate changes, call it p_1, and a counterfactual world without these changes, call it p_0. In the following, let us now see how to interpret these two probabilities.

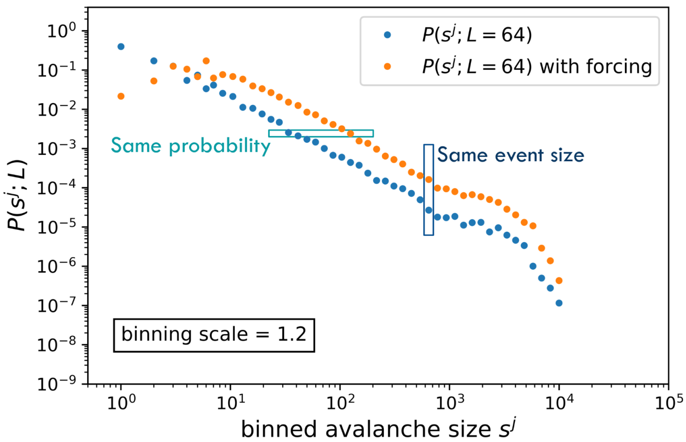

Figure 5: Comparison of avalanche size probabilities for the sand pile model of size $L = 64$: The orange curve shows the distribution when 4 grains are added at each step as opposed to 1 grain (shown in blue). Events of low magnitude become less likely whereas extreme events increase in probability.

4.1 Probabilistic approach to climate attribution science

Exactly as we did for the sand pile model, the probabilistic approach uses observations and computer simulations to determine the probabilities (p_0, p_1) and characteristics of extreme weather events in a world with and without climate change. Two commonly used measures in order to interpret these probabilities are the fraction of attributable risk FAR and the risk ratio RR [10]:

$$\boxed{FAR = 1 - \frac{p_0}{p_1}} \qquad \boxed{RR = \frac{p_1}{p_0}}$$

Let us illustrate their purpose by considering the following example:

Did we experience a specific dice outcome only because one has manipulated it?

One may distinguish the following manipulations:

A) A dice with faces $\{1, 2, 3, 4, 5, 7\}$ produces the outcome '7'.
In this case, the manipulation of the dice is a **necessary cause** for getting the outcome. Necessary causation is however not present in the context of weather extremes, since (most) events would in principle be possible without climate change.

B) A dice with faces $\{3, 3, 3, 3, 3, 3\}$ produces the outcome '3'.
Such a so-called **sufficient causation** is however also not suitable in the context of weather, since there exist no deterministic factors to produce weather extremes every time.

C) A dice with faces $\{1, 2, 4, 4, 4, 6\}$ produces the outcome '4'.
This corresponds to the to us relevant case and applying the two mentioned measures yields:

$$FAR = 1 - \frac{1/6}{3/6} = \frac{2}{3}$$

Here, a possible interpretation could be: *Out of 3 events that happened in the factual world, 2 would not have happened in the counterfactual one.*

$$RR = \frac{3/6}{1/6} = 3$$

Obtaining a risk ratio of 3, we may say: *Manipulating the dice increased the risk of getting a 4 by a factor of 3.*

We find the above logic for instance applied in an attribution study from 2017. Here, the researchers studied the attribution of the flood-inducing extreme precipitation in south Louisiana to climate change. In their publication it is stated that "the regional probability of 3-day extreme precipitation increases by more than a factor of 1.4 due to anthropogenic climate change" [8]. The study combines several computational climate models from different studies in order to ensure that the result is not particularly sensitive to underlying assumptions or the precise definition of the extreme rain event (see Fig. 6). So, the probabilistic approach estimates how a certain event type was made

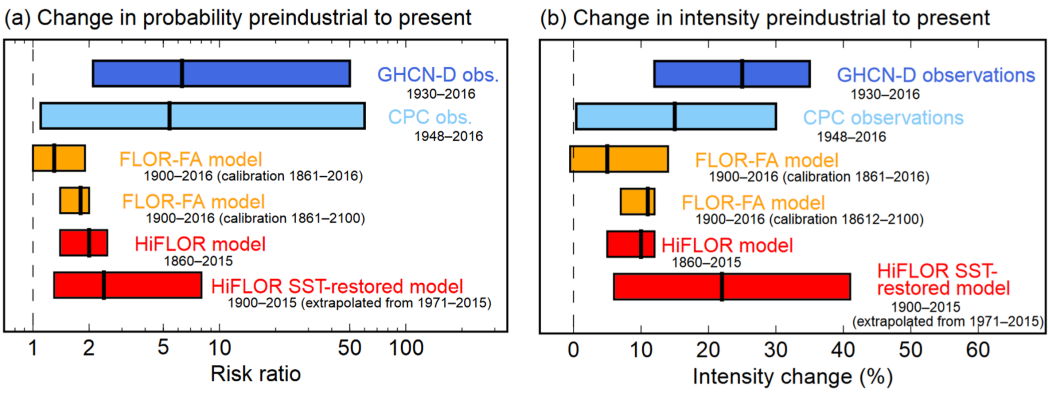

Figure 6: Attribution study of the flood-inducing extreme precipitation in south Louisiana in August 2016: As an average over different studies, it was found that human-caused climate change increased the probability of flood-inducing extreme rain events in South Louisiana by 40% and the intensity by 10%.

more likely or more severe due to anthropogenic climate change. It therefore deals with the characteristics of extreme precipitation (in a specific location) as more general event class. Now, in order to evaluate the influence of global warming on a unique, individual extreme weather event let us further consider the so-called pathway approach.

4.2 Pathway approach to climate attribution science

In the pathway approach, we consider an individual weather event that actually happened, at a specific time in a specific place, say a recent hurricane. We again want to compare to a counterfactual scenario. Therefore, one needs to simulate the event as accurate as possible and study how the event plays out in an alternative scenario where only some influences are altered. In practise, it is therefore important to validate the used computer simulation models with past events. That means that in the chain reaction that led to the observed weather extreme, the simulation is conditioned on for example the location at which the initial storm formed, the present wind directions and atmospheric pressures. From this initialization the simulation is run and one checks and check whether it correctly reproduces what in reality happened. Such a procedure is key to quantifying how accurate a model is. Now, to study how the hurricane would have evolved in a world without global warming, the same simulation can be run, adapting for instance the atmospheric temperature or the sea level to then ask the following questions:

- How might the hurricane's intensity have changed because of changes in SST or atmospheric humidity along its path?
- If the hurricane made landfall, how was the coastal flooding increased by long-term sea level rise?

The latter question was for example discussed in an attribution study from 2013, named *Simulations of Hurricane Katrina (2005) under sea level and climate conditions for 1900*. The researchers report that "Surge simulations suggest that flood elevations would have been **15 to 60 % lower** around 1900 than the conditions observed in 2005. This drastic change suggests that **significantly more flood damage** occurred in 2005 than would have occurred if sea level and climate conditions had been like those around 1900" [9].

5 Conclusion

Climate attribution science deals with a tough and important question: Is anthropogenic climate change to some extend responsible for extreme weather events? Clearly, attribution statements as discussed in chapter 4 give a crucial estimation towards how much damage could have been prevented, putting a definite price tag on human-induced global warming. Furthermore, attribution science also gives a concrete idea regarding the question how much more damage further global warming will cause.

The key challenge of any attribution science is to to obtain the counterfactual scenarios and is also knwon as the *fundamental problem of causal inference*. When manipulating a dice the cauterfactual world is easy to imagine. But concerning the hypothesis 'The school you attended is the reason for what subject you have chosen to study.', how would one create the counterfactuals? However, we have seen that in the context of climate attribution science simulations turn out to be extremely powerful and that the development and improvement of these simulations fundamentally relies on understanding the science and mechanisms behind an weather extremes. Eventually, many of these topics are still fields of very active research, promising further inside into climate attribution science for the future.

References

[1] Peter A. Stott, D. Stone, Myles Allen; *Human contribution to the European heat wave in 2003*, 2004, Nature, e-print: https://www.climateprediction.net/wp-content/publications/nature03089.pdf

[2] https://time.com/5652972/july-2019-hottest-month/

[3] https://edition.cnn.com/2019/10/31/us/california-fires-overview/index.html

[4] https://www.theguardian.com/world/2019/sep/07/hurricane-dorian-death-toll-missing-rescue

[5] https://www.bbc.com/news/world-europe-50401308

[6] https://sciencestruck.com/water-cycle-project-ideas

[7] K. Christensen, Nicholas R. Moloney; *Complexity and Networks: Complexity from the book Complexity and Criticality*, Imperial College Press, 2015, https://doi.org/10.1142/p365

[8] Van der Wiel, K., Kapnick, S. B., van Oldenborgh, G. J., Whan, K., Philip, S., Vecchi, G. A., Singh, R. K., Arrighi, J., and Cullen; *Rapid attribution of the August 2016 flood-inducing extreme precipitation in south Louisiana to climate change*, 2017, Hydrol. Earth Syst. Sci., 21, 897–921, e-print: https://www.hydrol-earth-syst-sci.net/21/897/2017/hess-21-897-2017.pdf

[9] Jennifer L. Irish, Alison Sleath, Mary A. Cialone, Thomas R. Knutson, Robert E. Jensen; *Simulations of Hurricane Katrina (2005) under sea level and climate conditions for 1900*, 2013, DOI 10.1007/s10584-013-1011-1, e-print: https://www.climatecentral.org/outreach/alert-archive/IrishSleath_etal2014.pdf

[10] A. Hannart, J. Pearl, F. E. L. Otto, P. Naveau, M. Ghi; *Causal Counterfactual Theory For The Attribution Of Weather And Climate-Related Events*, 2016, DOI:10.1175/BAMS-D-14-00034, e-print: https://journals.ametsoc.org/doi/pdf/10.1175/BAMS-D-14-00034.1

[11] National Academies of Sciences, Engineering, and Medicine; *Attribution of Extreme Weather Events in the Context of Climate Change*, 2016, Washington, DC: The National Academies Press., e-print: https://doi.org/10.17226/21852