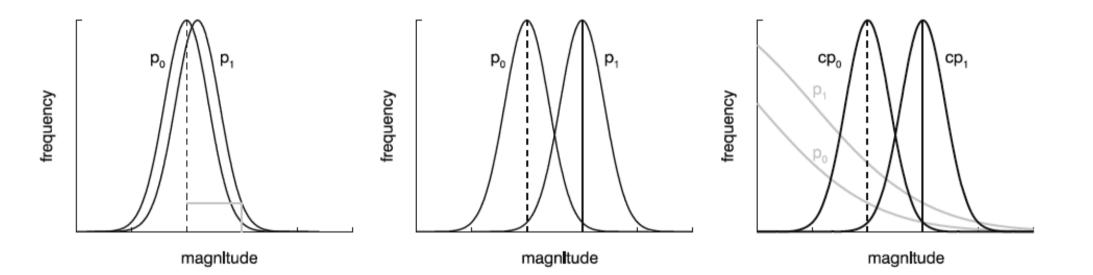


STORYLINE APPROACH TO EXTREME EVENT CHARACTERIZATION



Professor Ted Shepherd, Grantham Chair of Climate Science Department of Meteorology, University of Reading



Established by the European Commission

Pearl's "Ladder of Causation"

JUDEA PEARL winner of the turing award AND DANA MACKENZIE

THE

ΒΟΟΚ ΟΓ

WHY



THE NEW SCIENCE OF CAUSE AND EFFECT

- Association (correlation):
 - Climate system is non-stationary, and sampling is incomplete
 - Aggregation and conditioning always involves assumptions
- Intervention:
 - Not possible, though there are natural experiments (e.g. volcanic eruptions)
- Counterfactuals:
 - Requires imagination; by definition, not "real" (and cannot be created)
 - Where theory and models come in; need to build *evidence*
- Conclusion: primacy of causal reasoning
 - But it's very hard to prove anything!

EXTREME EVENTS (A SOBEL AND SJ CAMARGO, SECTION EDITORS)

A Common Framework for Approaches to Extreme Event Attribution

Theodore G. Shepherd¹

PROCEEDINGS A

royalsocietypublishing.org/journal/rspa

2019 Research Storyline approach to the construction of regional climate change information

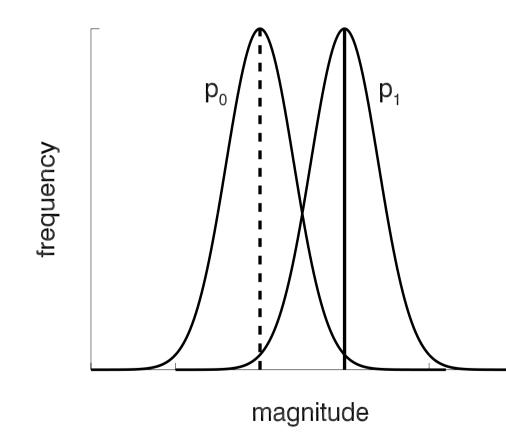
Theodore G. Shepherd

The heart of the matter

- Every extreme event is unique
 - Heraclitus: "No man ever steps in the same river twice"
- We can either consider it as a singular event (case study perspective) or create an 'event class' to produce a large sample size (statistical perspective)
 - The first approach sacrifices generalizability for specificity
 - The second approach: the opposite
- This sort of dichotomy, between specificity and generality, occurs in many areas of science (even weather vs climate)
- The concept of 'extreme' has two distinct meanings: can be extreme in *impact*, or extreme in *rareness*
 - Only the latter lends itself to a statistical approach
 - The two are not equivalent! (e.g. van der Wiel 2020 ERL)

Event attribution: Case of a large shift in the PDF

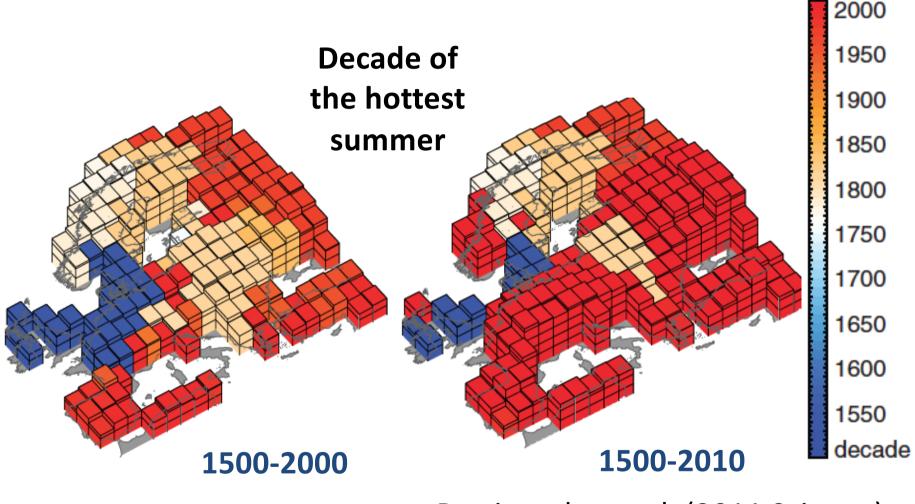
- p₁ is factual, p₀ is counter-factual (i.e. without climate change)
- What used to be extreme, is now normal
- Like a criminal investigation: guilty beyond reasonable doubt



- Has predictive power for individual realizations (events)
- Generally applies for sufficiently large time and space averages of land surface temperature

Shepherd (2016 CCCR)

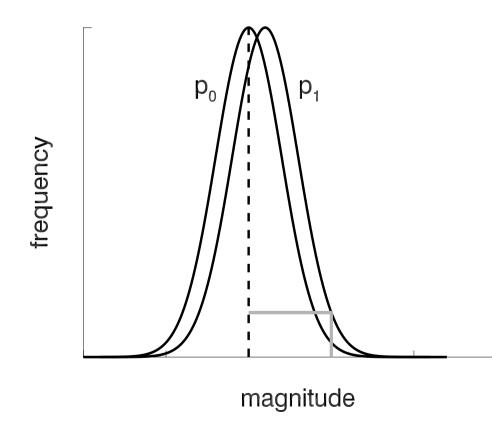
• Example: Adding ten years to a 500-year record completely redrew the temperature record map of Europe



Barriopedro et al. (2011 Science)

Event attribution: Case of a small shift in the PDF

- Relative change in frequency of extremes (y-axis) is large, but relative change in magnitude (x-axis) is not (gray lines)
- Can lead to apparently conflicting results depending on the perspective taken (Otto et al. 2012 GRL)

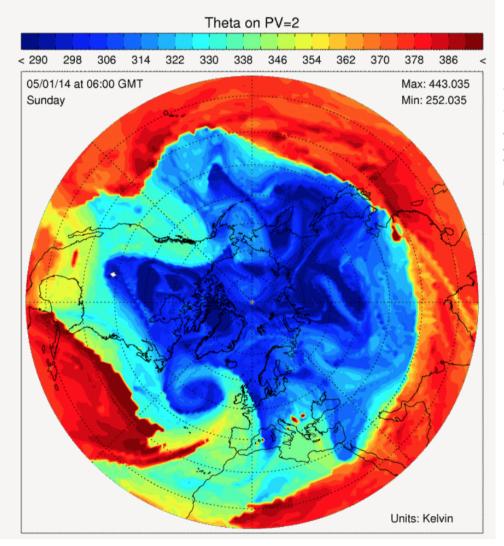


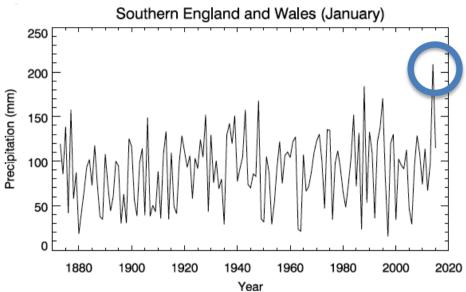
- But small relative changes in magnitude tend to matter for extremes
- Requires extreme variability to get the observed extreme
- Multiple causal factors; involves a causal narrative (i.e. storyline)

Shepherd (2016 CCCR)

• Consider the winter of 2013/2014

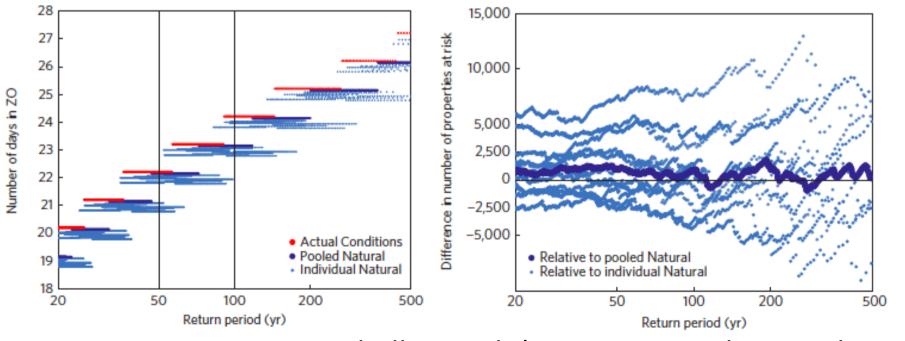
- Extreme cold over central USA, record precipitation in the UK





The proximate explanation for the UK was the "stuck" jet stream, but there is no accepted view on whether this is more or less likely under climate change (let alone by how much)

- Flooding in southern England in January 2014 was associated with this strong and persistent jet stream
- Left: Estimate of change in likelihood of this dynamical regime (ZO state) from weather@home; either no change, or very large change, depending on the estimated change in SSTs
- Right: The resulting circulation changes make the difference between increased and decreased flood risk



Schaller et al. (2016 Nature Climate Change)

 Table 24.1. Summary of results for Explaining Extreme Events of 2013 from a Climate

 Perspective, with the role of anthropogenic climate change (increased, decreased, no evidence)

 noted for each event. Specific papers examining the event are noted in parenthesis.

	Summary Statement	Anthropogenic Influence Increased Event Likelihood or Strength	Anthropogenic Influence Decreased Event Likelihood or Strength	Anthropogenic Influence Not Found or Uncertain	Total # of Papers
Heat	Long duration heat waves dur- ing the summer and prevailing warmth for annual conditions are becoming increasingly like- ly due to a warming planet, as much as 10 times more likely due to the current cumula- tive effects of human-induced climate change, as found for the Korean heat wave of sum- mer 2013.	Australia Heat [Arblaster et al., King et al. Knutson et al. (a), Lewis et al., Perkins et al.] Europe Heat (Dong et al.) China Heat (Zhou et al.) Japan Heat (Imada et al.) Korea Heat (Min et al.)			9
Cold	Prolonged cold waves have become much less likely, such that the severely cold 2013 winter over the United King- dom was perhaps the most remarkable event of all those studied in 2013—its probability of occurrence may have fallen 30-fold due to global warming.		UK Cold Spring (Christidis et al.)		I
Heavy Precipitation	Extreme precipitation events of 2013 were found to have been much less influenced by human-induced climate change than extreme temperature events.	U.S. Seasonal Precip [Knutson et al. (b)] India Precip (Singh et al.)	U.S. Northern Colorado Precip (Hoerling et al.)	Southern Europe Precip (Yiou and Cattiaux) Central Europe Precip (Schaller et al.)	5
Drought	Droughts are highly complex meteorological events, and re- search groups analyzed different factors that influence droughts such as sea surface tempera- ture, heat, or precipitation.	New Zealand Drought (Harrington et al.)		U.S. California Drought* (Funk et al., Wang and Schubert**)	3
	Swain et al. found evidence that atmospheric pressure patterns increased, but the influence on the California drought remains uncertain.	Large-scale atmo- spheric conditions linked to the U.S. Cali- fornia drought (Swain et al.***)			I
Storms	There was no clear evidence for human influence on any of the three very intense storms examined, which included a surprising winter-like storm during autumn in the Pyr- ences, an extreme blizzard across the U.S. High Plains, and Cyclone 'Christian' that delivered damaging winds			Cyclone Christian (von Storch et al.) Pyrenees Snow (Anel et al.) U.S. South Dakota Blizzard (Edwards et al.)	3
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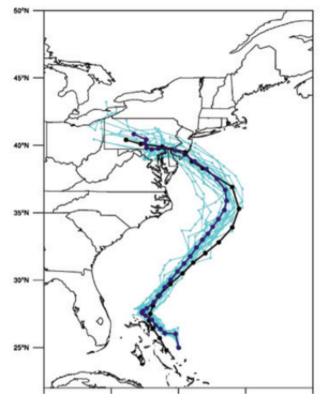
C

The conventional probabilistic approach to extreme event attribution is challenged by circulation-related extremes, and can easily lead to a null result (especially if uncertainties are factored in)

This does not mean there was no effect!

BAMS Extremes Report for 2013 (2014)

- The normal scientific null (or prior) hypothesis is "no effect"
 - Given the magnitude of natural variability, model uncertainty, and the limited observational record, one may not be able to reject that null hypothesis, even if there were a signal
 - Failure to reject the null hypothesis does not prove the null hypothesis
- Perhaps our null (or prior) hypothesis should be the robust aspects of anthropogenic climate change?
 - We are very confident of those aspects; it seems rather perverse to pretend we don't know about them
 - If we wait until the observed trends are unambiguous, it will be much too late
 - A reinsurance firm would take a precautionary approach; should actionable climate science be any different?



- Hurricane Sandy (2012) was unusual only in its rapid westward steering and its merger with an extratropical storm, both the result of a strongly deformed jet stream
- It seems almost meaningless to ask if such a fluke event would become more likely in the future
- But we do know that sea level will be higher, and storms will hold more moisture
- Thus we can legitimately ask (and plausibly answer) the counterfactual questions (Trenberth et al. 2015 Nature Clim. Change):
 - How much were the impacts of Sandy increased by climate change?
 - How much worse might they be in the future?
- Singular causation is a perfectly sensible philosophical concept; aggregation (as in randomized control trials) has its own problems (Nancy Cartwright, Univ Durham Working Paper, 2017)
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Learning from samples of one or fewer (March et al. 1991 Org. Sci.) ullet

10 August 2003

The summer 2003 heat wave in central France ullet

1 August 2000

8/10/2003 8/1/2000 NDVI': -0.35 NDVI': -0.00 321-RGB 8/10/2003 8/1/2000 +20 C +11 C 500 m ASTER T_R

42°C

32°C

47°C

There is (conditional) information here!

Zaitchik et al. (2006 Int. J. Clim.)

NDVI



Surface Temperature

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27°C

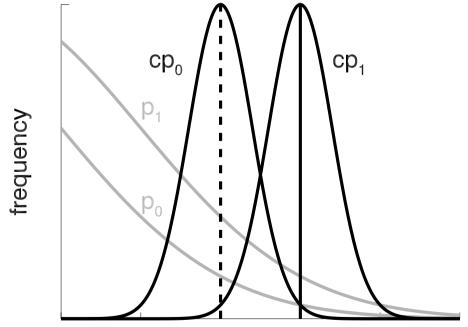
The "storyline" approach: Dynamically conditioned attribution

• Formulation:

$$\frac{p_1(E,C)}{p_0(E,C)} = \frac{p_1(E|C)}{p_0(E|C)} \times \frac{p_1(C)}{p_0(C)}$$

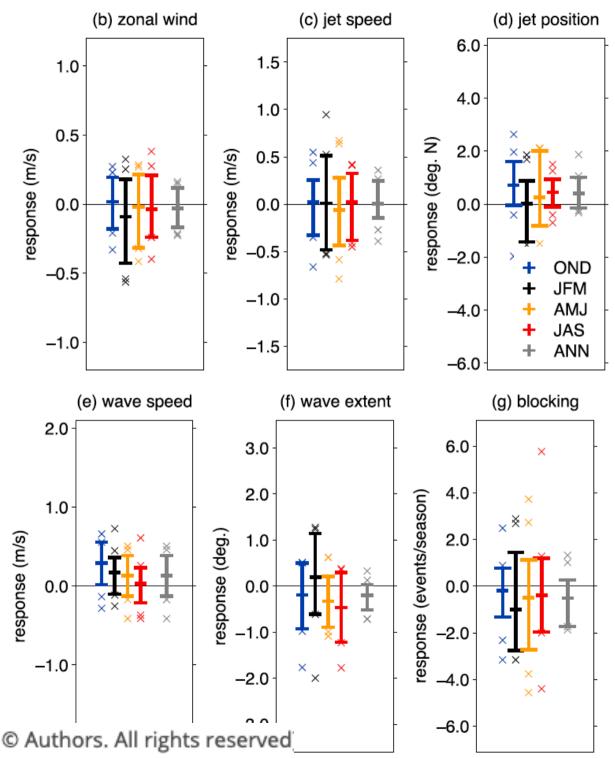
(NAS 2016)

E is the extreme of interest,
 C the synoptic situation
 conducive to that extreme



magnitude Shepherd (2016 CCCR) © Authors. All rights reserved

- The conditional probability ratio represents the purely thermodynamic effects of climate change, given the synoptic situation
- Will have high signal-to-noise, even for a single event (sufficient causation)
- The second factor may be negligible or highly uncertain (Trenberth, Fasullo & Shepherd 2015 Nature CC)

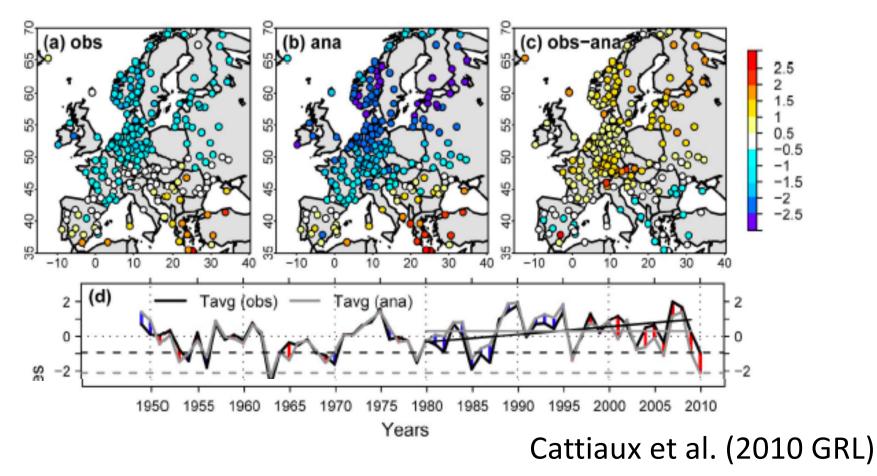


Example: The projected response of key dynamical quantities over the North America/North Atlantic sector to climate change, in the near term (2020-2044 relative to 1980-2004), is highly uncertain

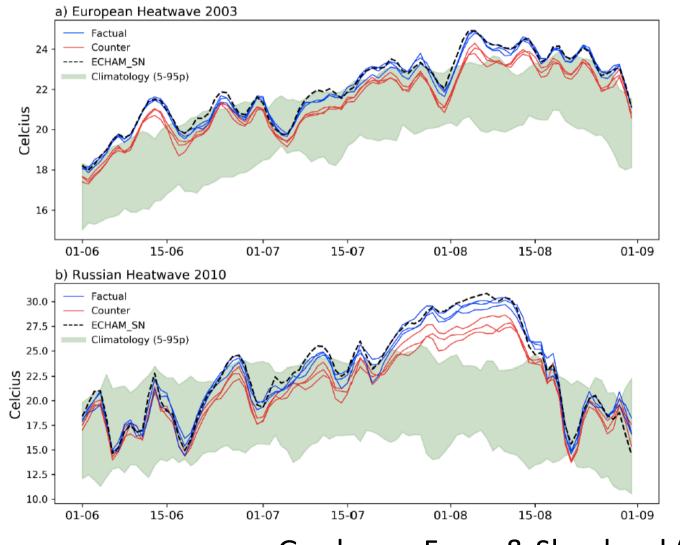
Assume it is zero is a reasonable null hypothesis

Barnes & Polvani (2015 J. Clim.)

- **Conditional attribution:** The cold European winter of 2010 was less cold than it would have been, because of climate change
- An otherwise undetectable effect was identified by comparing the observed state with the state that would have occurred under the same circulation regime (the "analogue" state)



 Nudging of winds within an atmospheric model to reanalysis allows historical heat waves, and the influence of anthropogenic warming, to be followed at a daily resolution

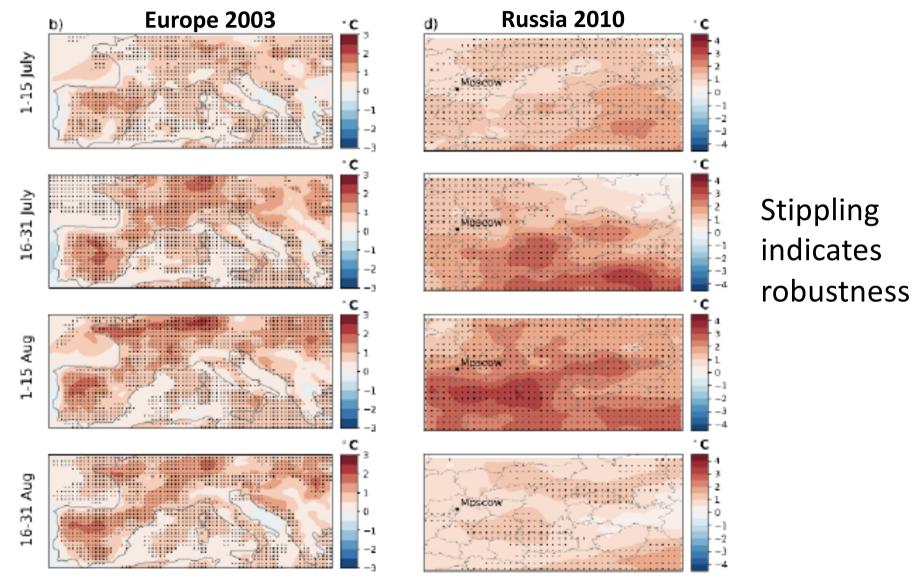


Difference between blue and red curves represents the anthropogenic warming

van Garderen, Feser & Shepherd (GMD, submitted)

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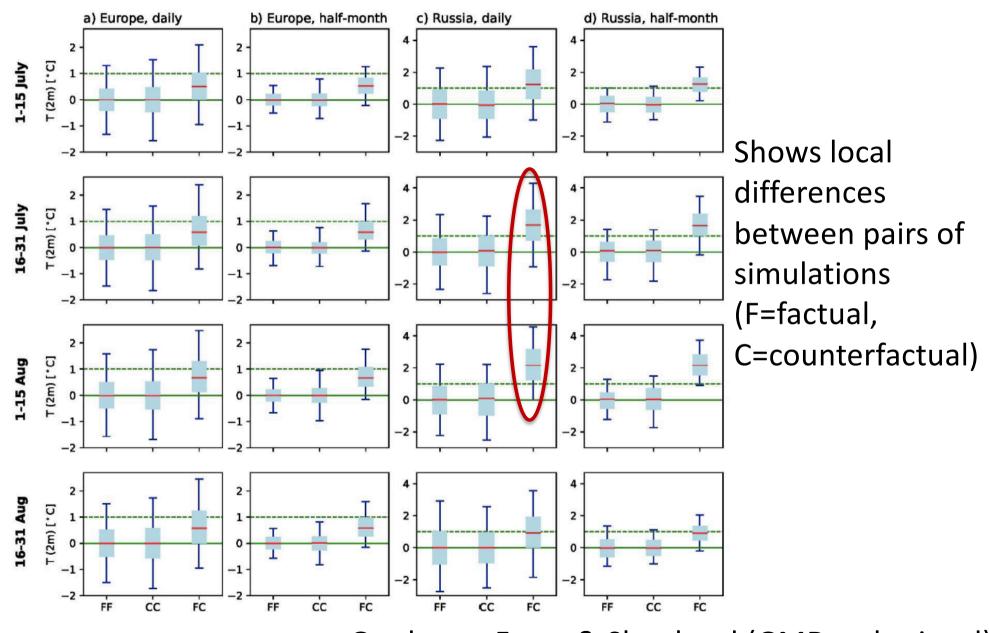
• By constraining the circulation, the anthropogenic warming (contours) can also be quantified at a local spatial scale



van Garderen, Feser & Shepherd (GMD, submitted)

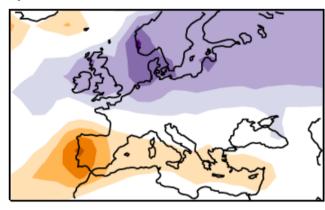
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• Anthropogenic warming was strongly enhanced in Russian event



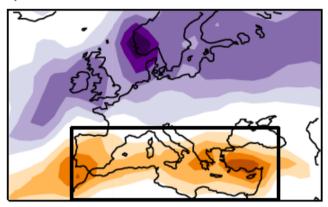
© Authors. All rights reserved van Garderen, Feser & Shepherd (GMD, submitted)

- Four storylines of cold-season Mediterranean drying
 - So far as we know, any one of these could be true
 - a) low tropical amp + strong vortex

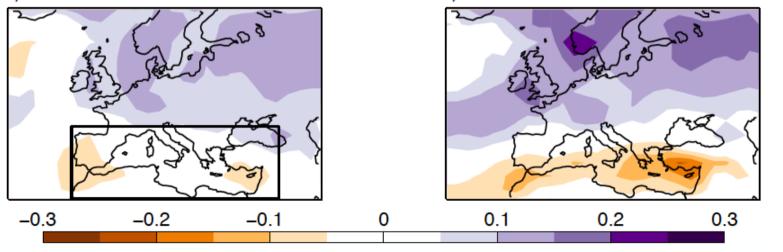


c) low tropical amp + weak vortex

b) high tropical amp + strong vortex

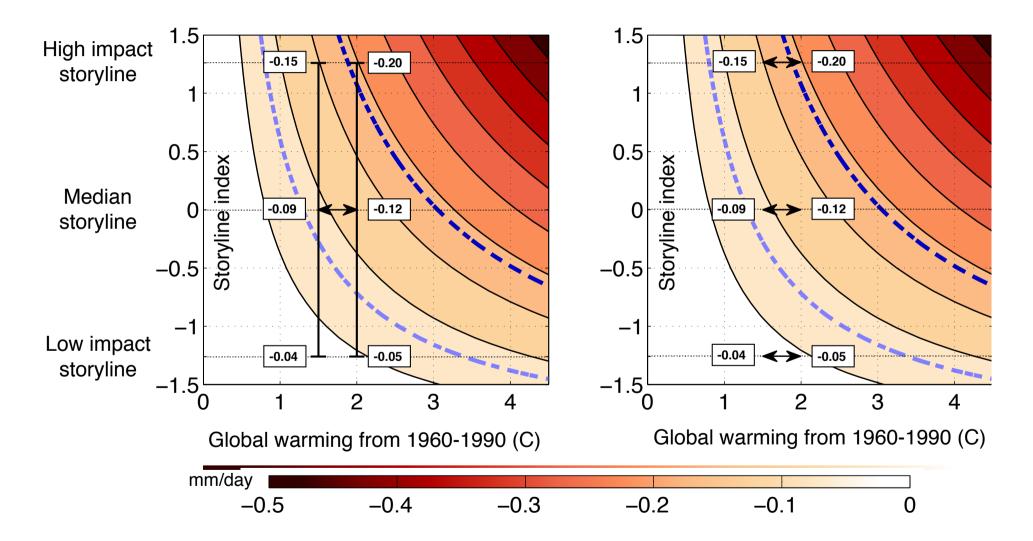


d) high tropical amp + weak vortex



^{mm/day/K} Zappa & Shepherd (2017 J. Clim.)

 Traditional (left) vs storyline (right) view of the difference in Mediterranean wintertime drying for different warming levels



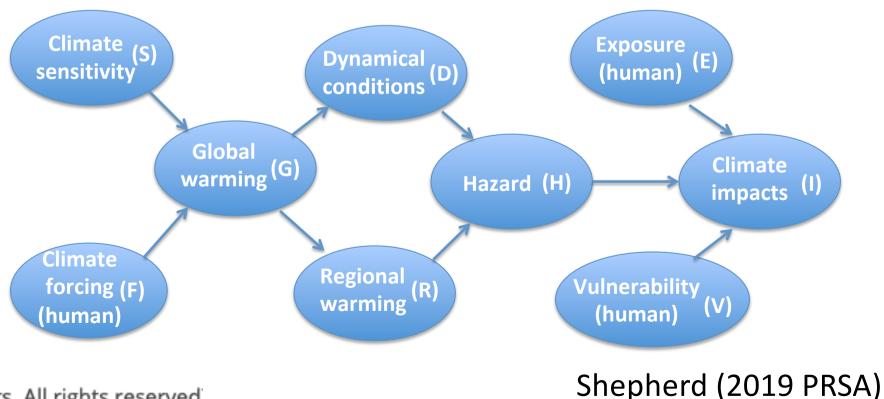
Adapted from Zappa & Shepherd (2017 J. Clim.)

• Storylines can be regarded as a 'truncated factorization' of the joint probability of a Bayesian causal network (Pearl 2009)

$$P(x_1,...,x_n) = \prod_j P(x_j | pa_j)$$

obtained by imposing a particular set of x_i 's as a counter-factual

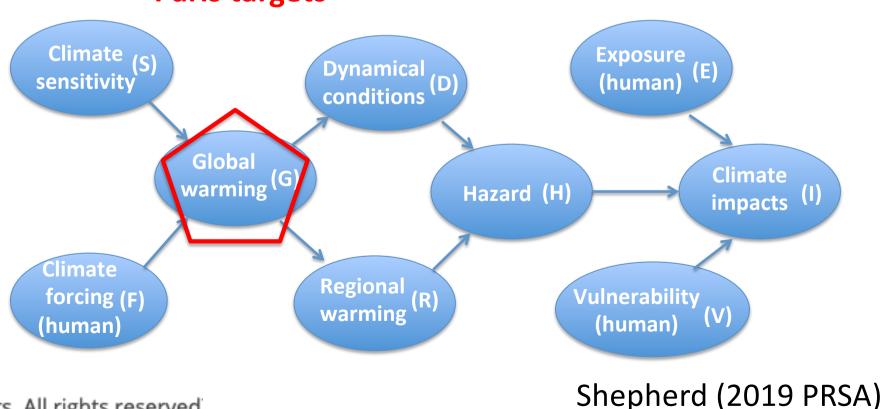
• Here pa_i are the 'parent' factors influencing x_i



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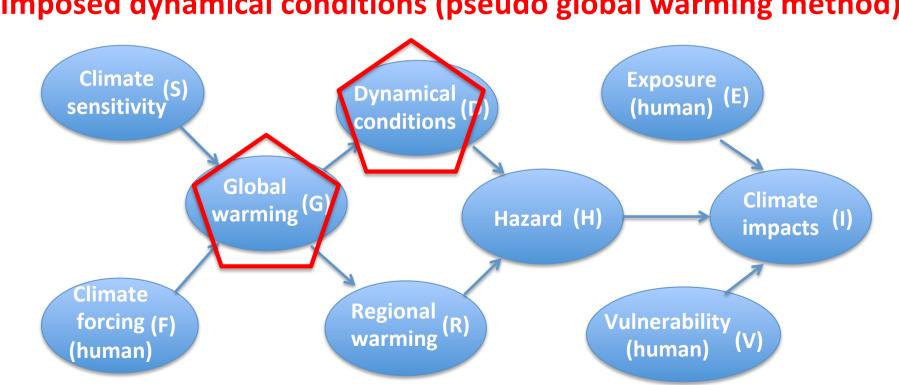


Paris targets

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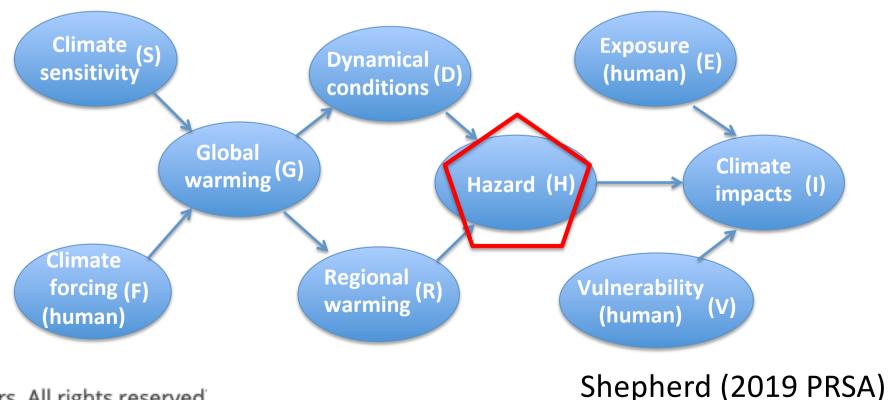
Shepherd (2019 PRSA)

Imposed dynamical conditions (pseudo global warming method)

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$$P(x_1,...,x_n) = \prod_j P(x_j | pa_j)$$

obtained by imposing a particular set of x_i 's as a counter-factual



Stress tests for resilience (WGII perspective)

Summary

- The usual way climate scientists characterize extreme events (i.e. probabilistically) puts a premium on avoiding Type 1 errors
 - Blurs out crucial details of events; may not relate to impacts

Reliability is sought at the price of informativeness

- Storylines provide a scientific language for expressing the uncertainties in climate change, without losing sight of the robust aspects, thereby addressing avoidance of Type 2 errors
 - Allows the incorporation of dynamical reasoning, anchored in physical theory and in hierarchies of models
 - Also allows consideration of non-climate anthropogenic
 factors, which can be the main drivers of climate vulnerability
- Need to relate to people's context and concerns, which are *local*
 - A manifestation of the generic tension between individual case studies and statistical analyses that pool all data, which arises in many areas of science