Identifying a human role in extreme weather events

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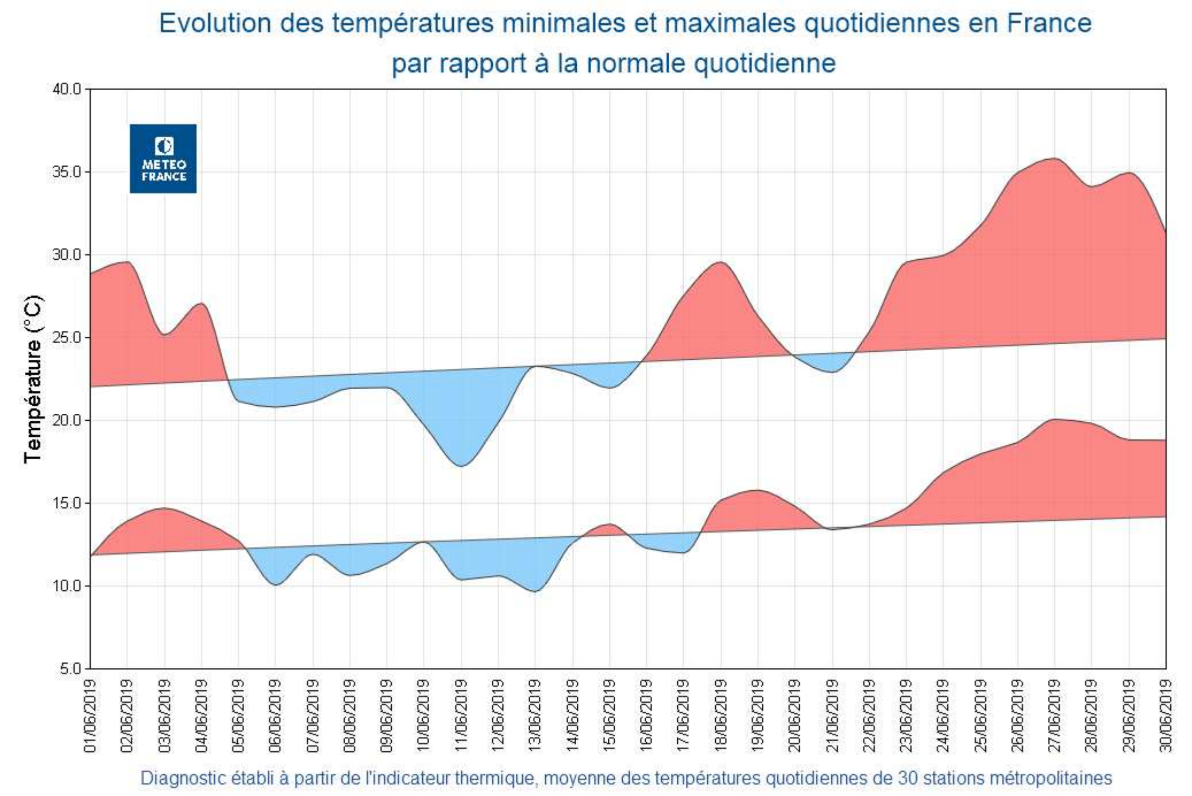
2.1. France, June 2019

Daily maximum and minimum temperature averaged across France



Evolution des températures minimales et maximales quotidiennes en France
par rapport à la normale quotidienne

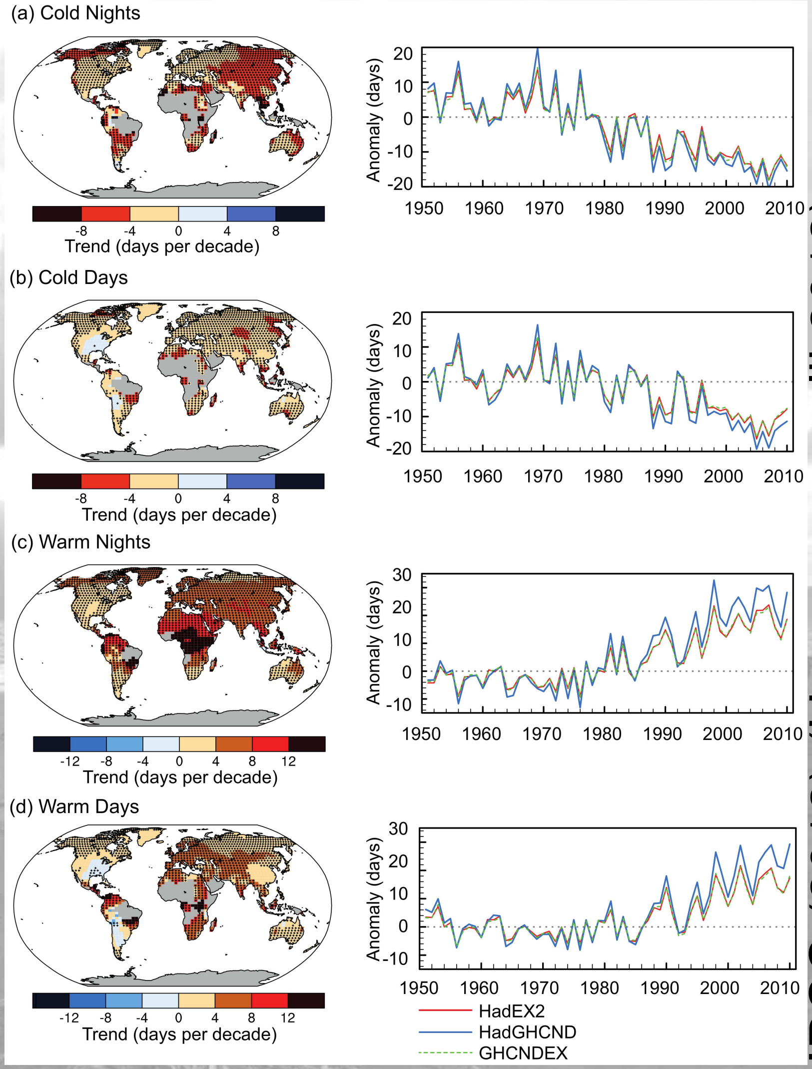
Diagnostic établi à partir de l'indicateur thermique, moyenne des températures quotidiennes de 30 stations métropolitaines

Météo-France

Guess when the International Meeting on Statistical Climatology occurred in Toulouse, southwestern France?

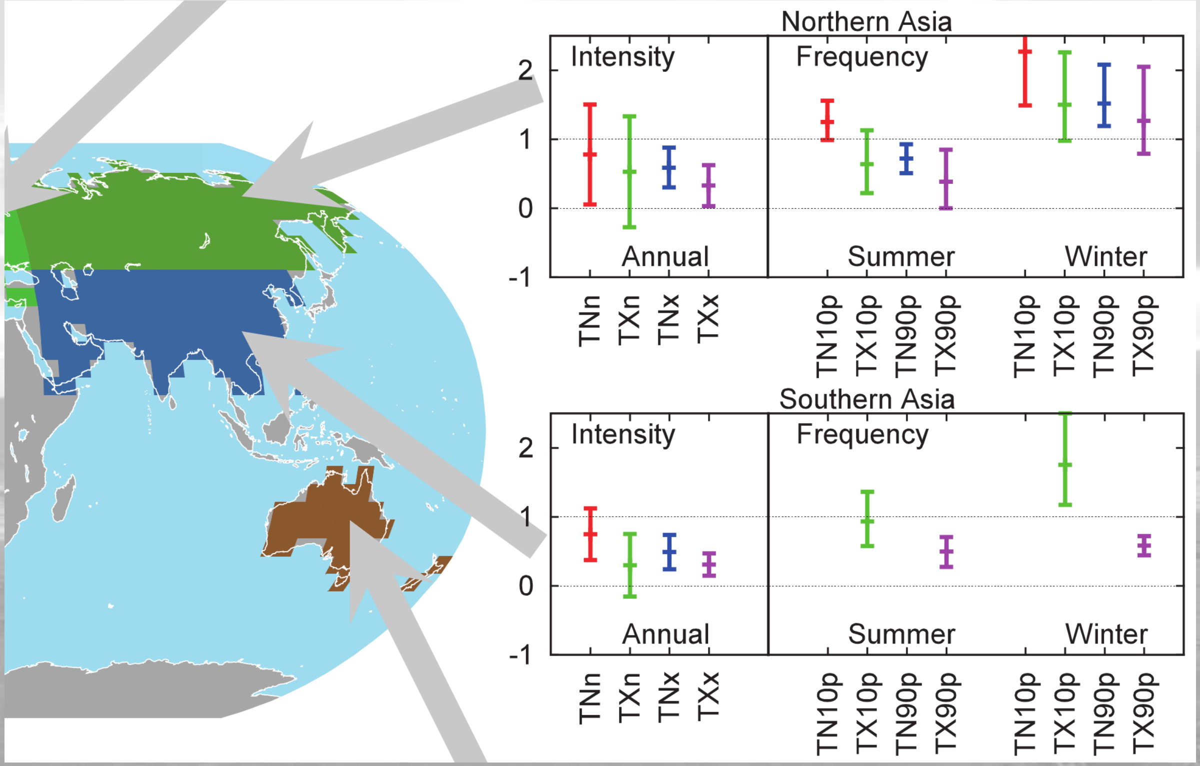
2.2. Extreme weather seems to be common now

- In the context of human-induced climate change, you might ask: *“Are we to blame for this weather event?”*
- Can we address that question?



IPCC (2013) (Hartmann et alii 2013)

2.3. What does standard detection and attribution tell us?



IPCC (2013) (Bindoff et alii 2013)

- Hard to apply at small spatial scales
- Hard to apply for rare events
  - How do you measure the trend in 1-in-100-year events in 50 years of observations?

2.4. Causative philosophy

Necessary causation:

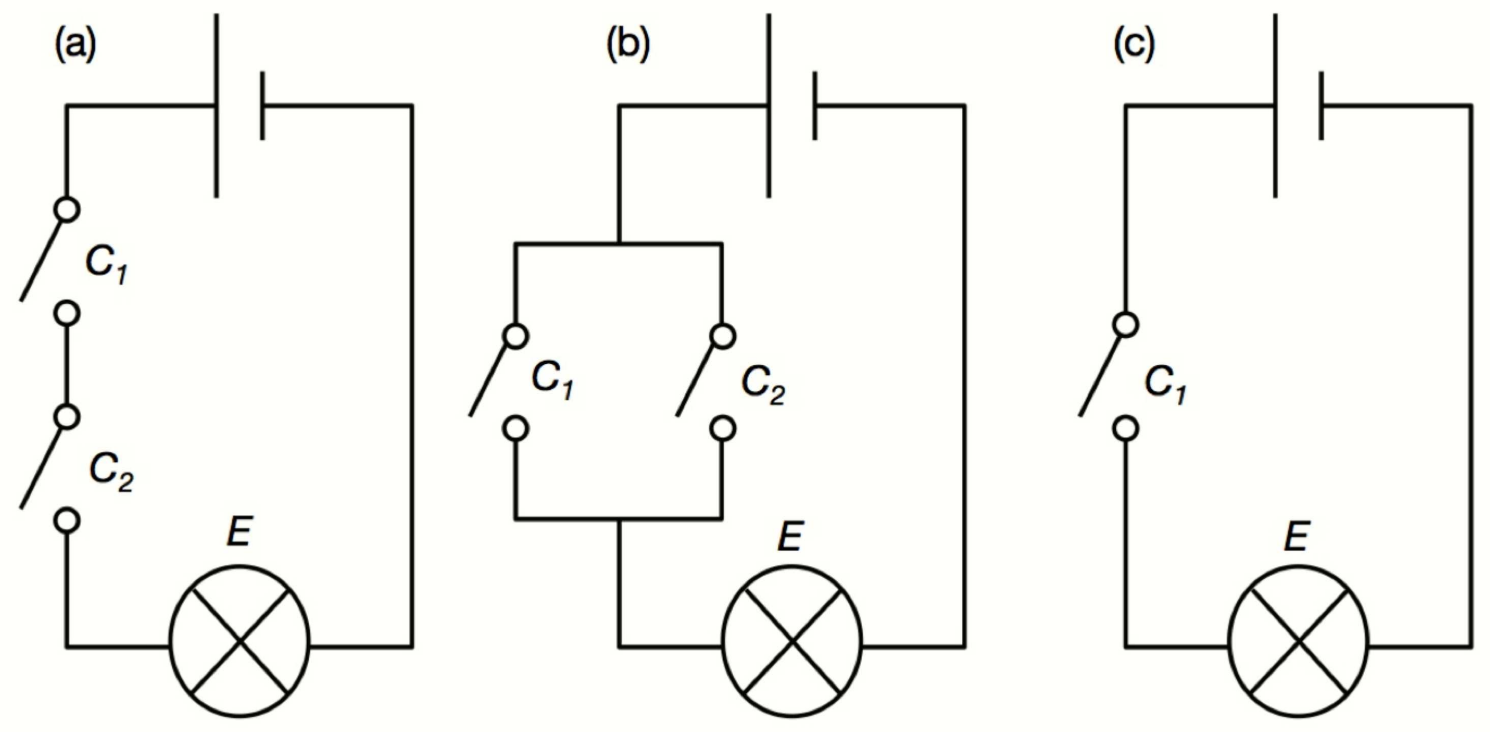
Turning Switch C_1 on is necessary but not sufficient

Sufficient causation:

Turning Switch C_1 on is sufficient but not necessary

Necessary and sufficient:

Turning switch C_1 on is both necessary and sufficient

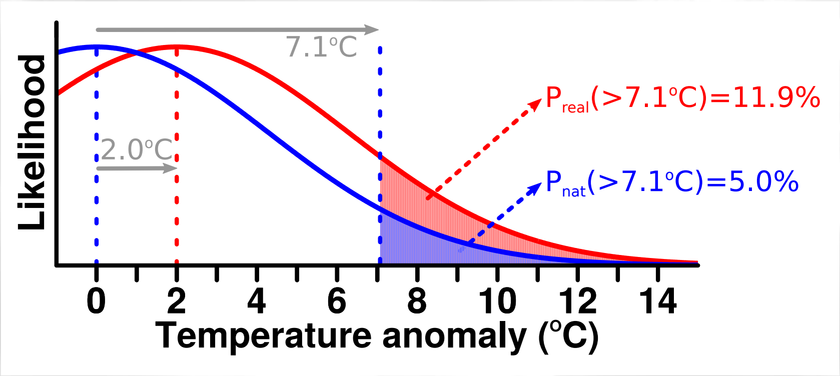


Hannart and Naveau (2016)

- But the climate system is much more complex than that

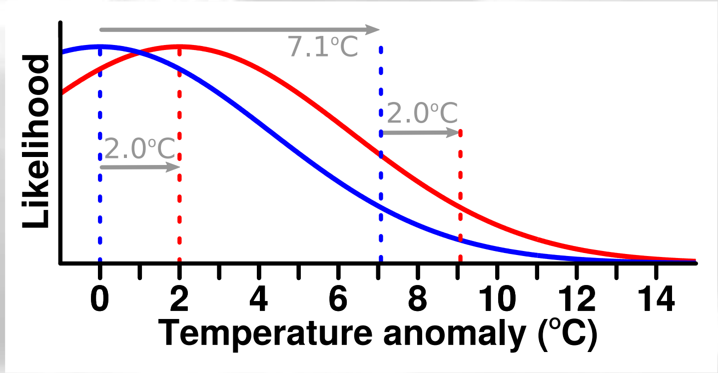
2.5. Causative framing

Change in probability

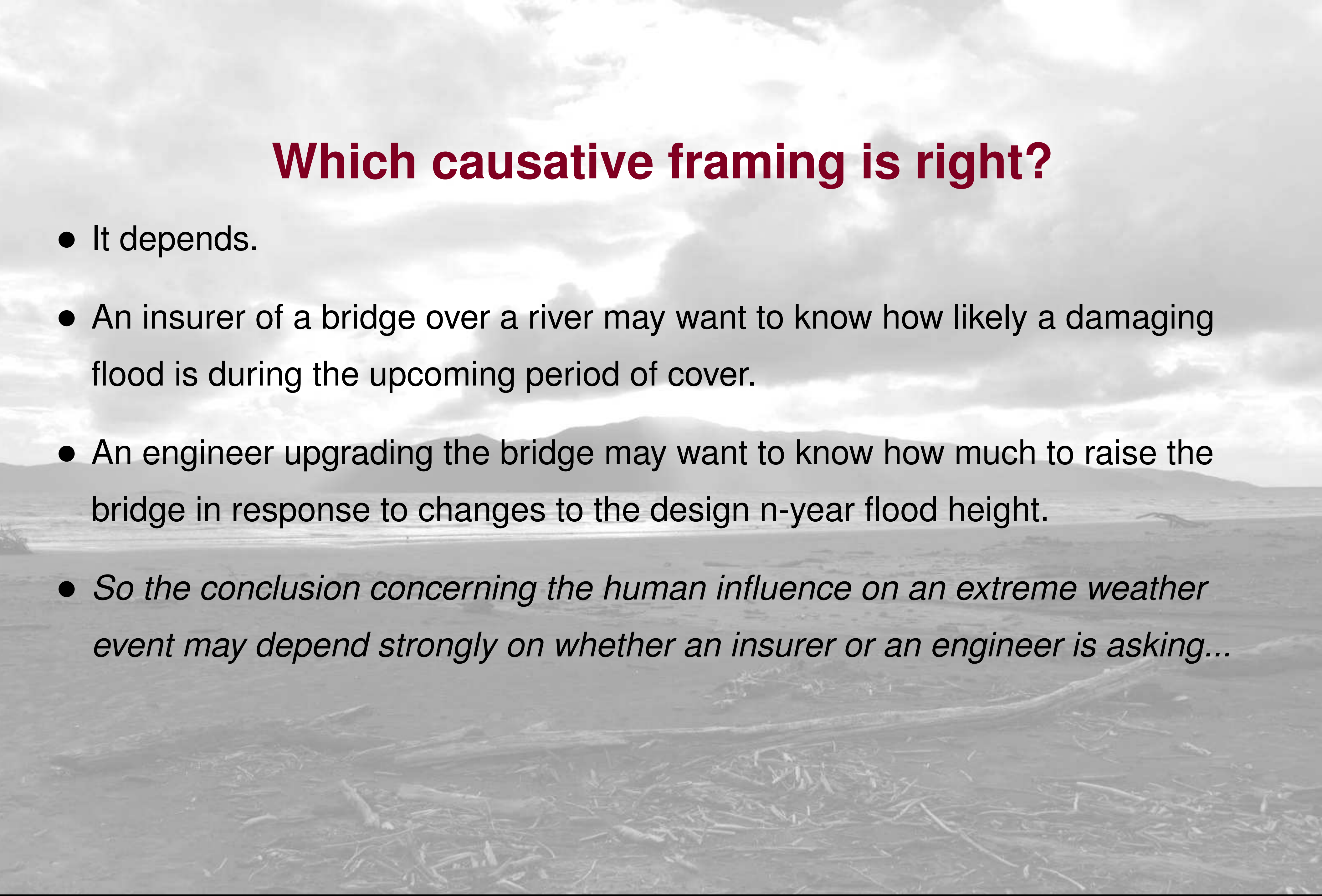


- "risk ratio" measure: $RR = \frac{P_{real}}{P_{nat}}$
- For above, $RR = \frac{0.119}{0.050} = 2.4$, chance has more than doubled
- "fraction attributable risk" measure: $FAR = 1 - \frac{P_{nat}}{P_{real}} = 1 - \frac{1}{RR}$
- For above, $FAR = 0.58$, so 58% of event occurrence due to emissions

Change in magnitude

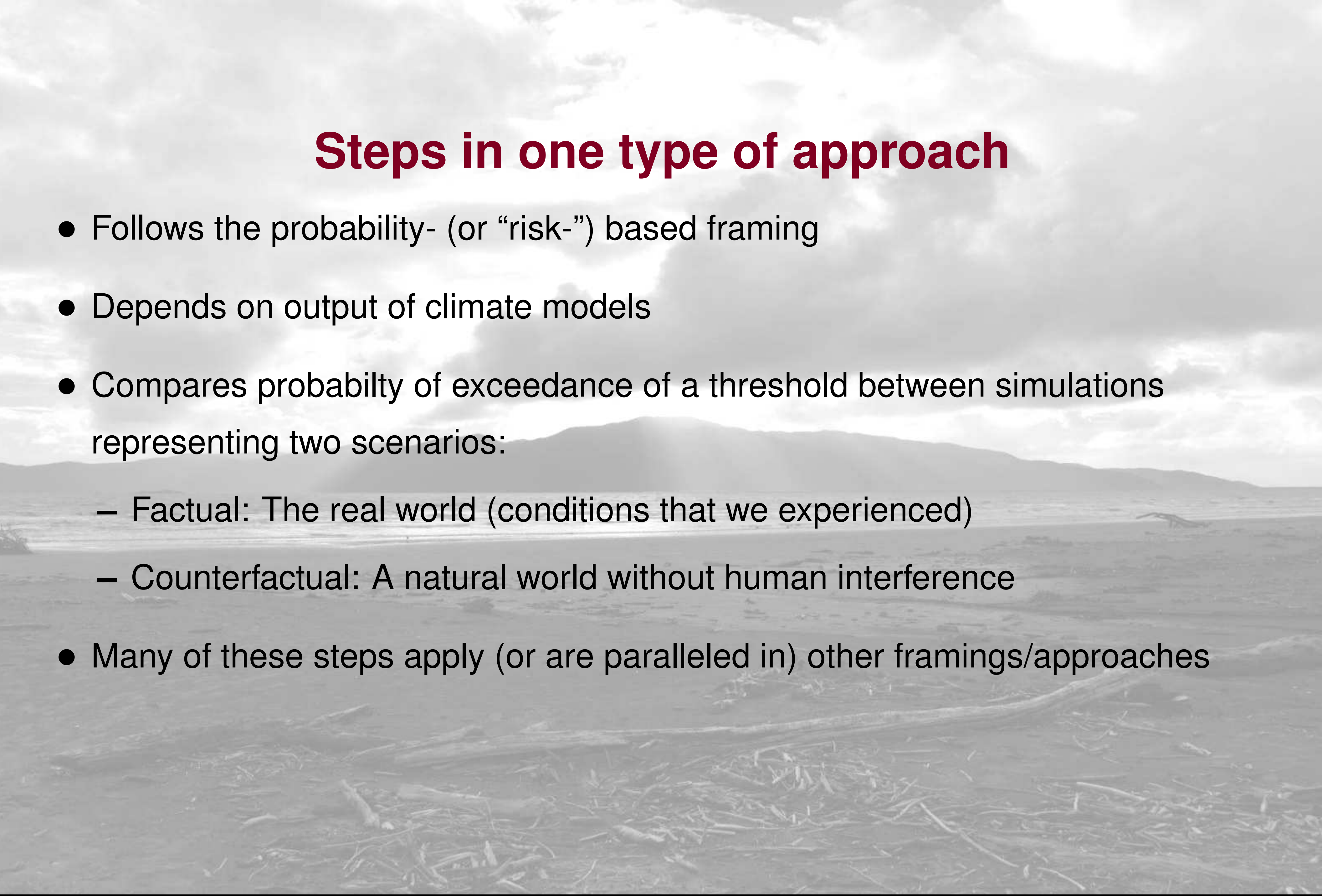


- For above, $\frac{2.0}{7.1} = 0.28$, so 28% of anomalous magnitude due to emissions
- 28% does not sound like much
  - Contrast with "chance increased by 2.4 times" and "58% of event occurrence" statements at left
  - *Causative framing matters*



Which causative framing is right?

- It depends.
- An insurer of a bridge over a river may want to know how likely a damaging flood is during the upcoming period of cover.
- An engineer upgrading the bridge may want to know how much to raise the bridge in response to changes to the design n-year flood height.
- *So the conclusion concerning the human influence on an extreme weather event may depend strongly on whether an insurer or an engineer is asking...*



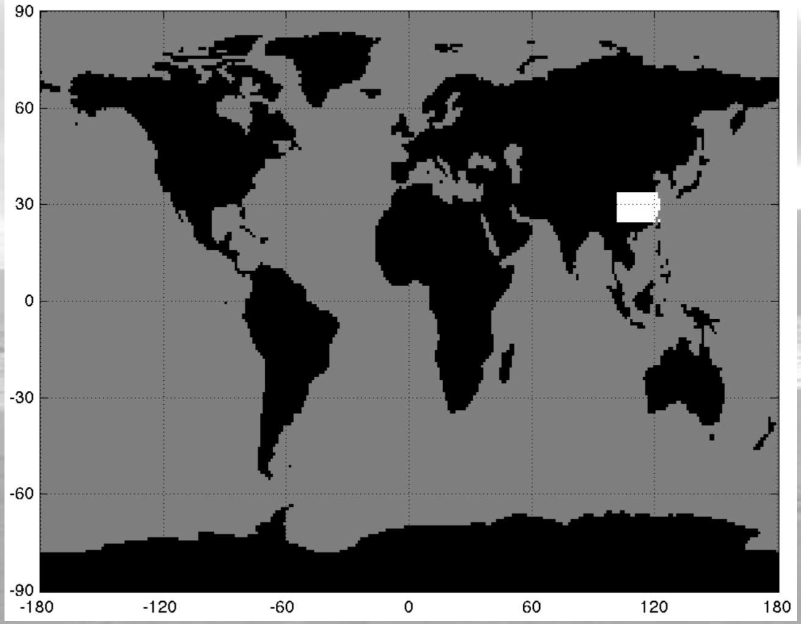
Steps in one type of approach

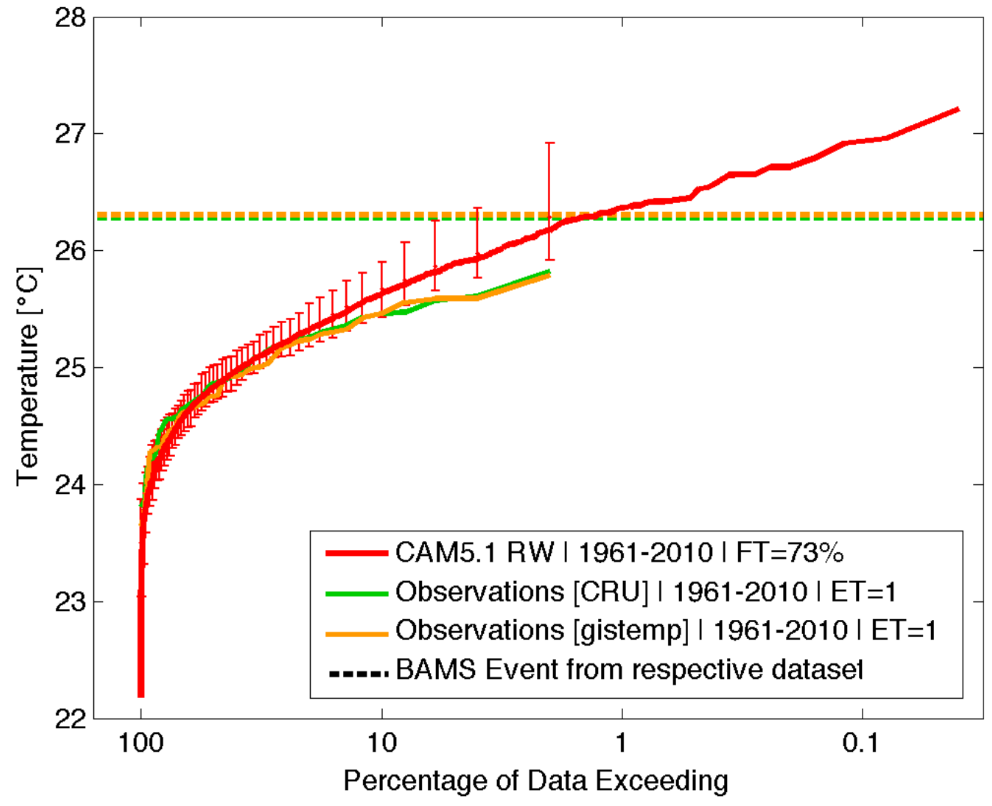
- Follows the probability- (or “risk-”) based framing
- Depends on output of climate models
- Compares probabilty of exceedance of a threshold between simulations representing two scenarios:
  - Factual: The real world (conditions that we experienced)
  - Counterfactual: A natural world without human interference
- Many of these steps apply (or are paralleled in) other framings/approaches

2.6. Step #1: Identify an event

Was the event “extreme”?

Temperature over central eastern China, July-August 2013

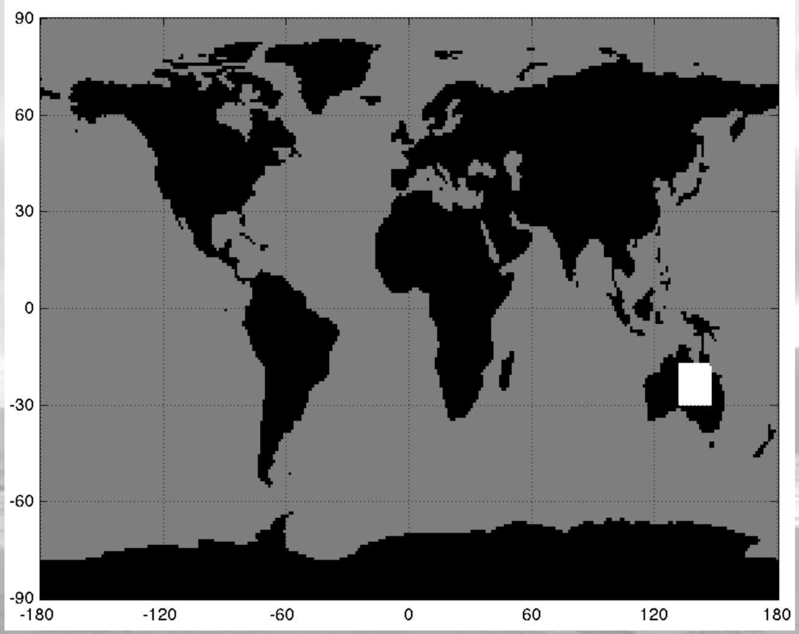


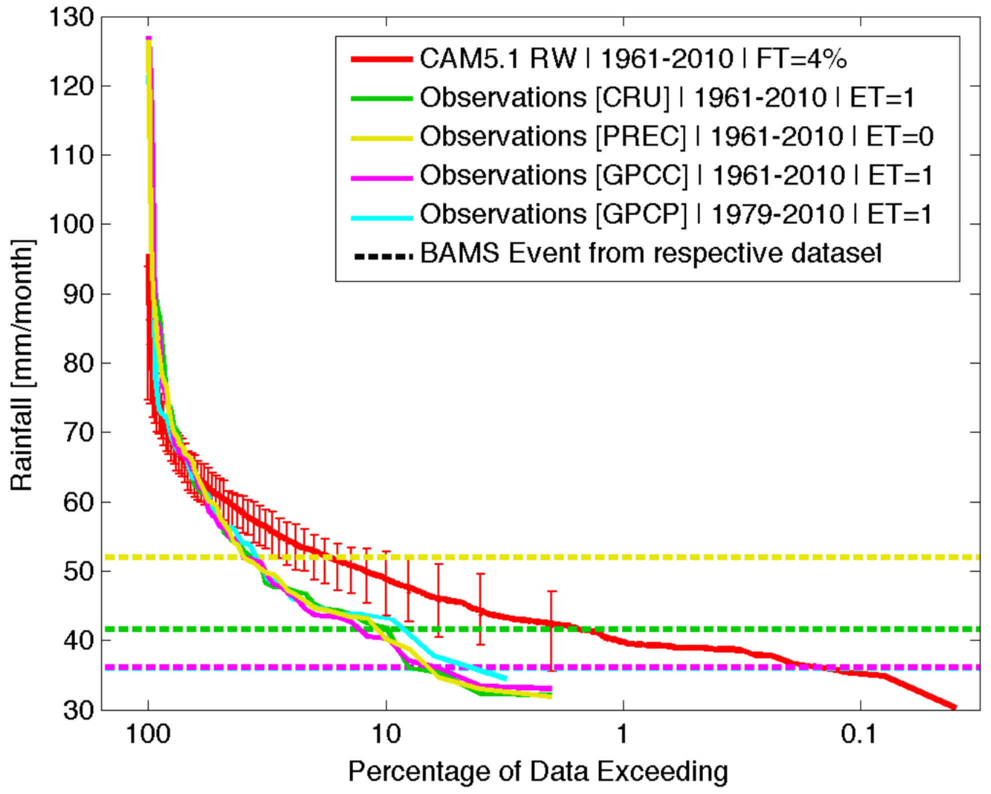


Angélil et alii (2017)

Was this event “extreme”?

Precipitation over inland eastern Australia, January-December 2013



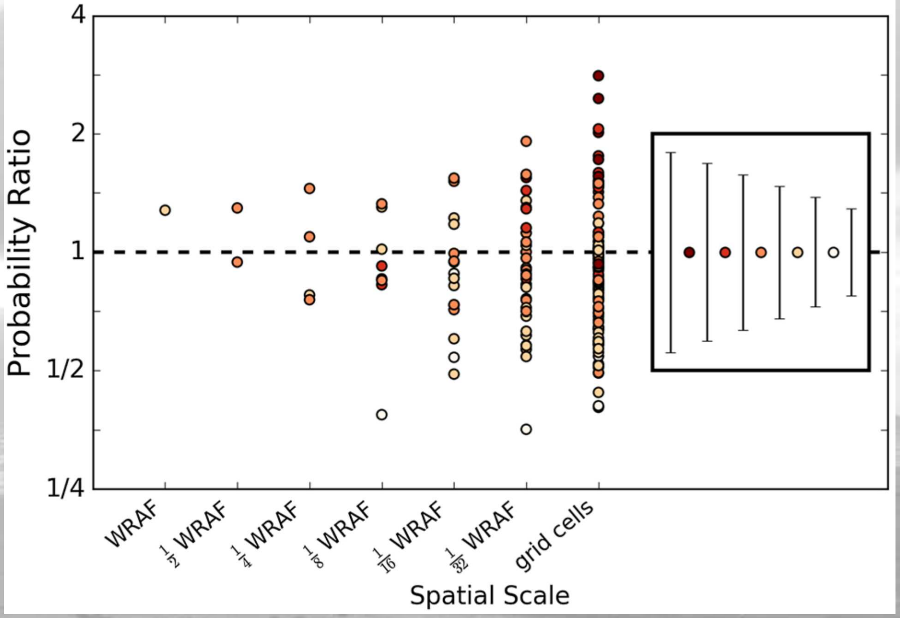


Angélil et alii (2017)

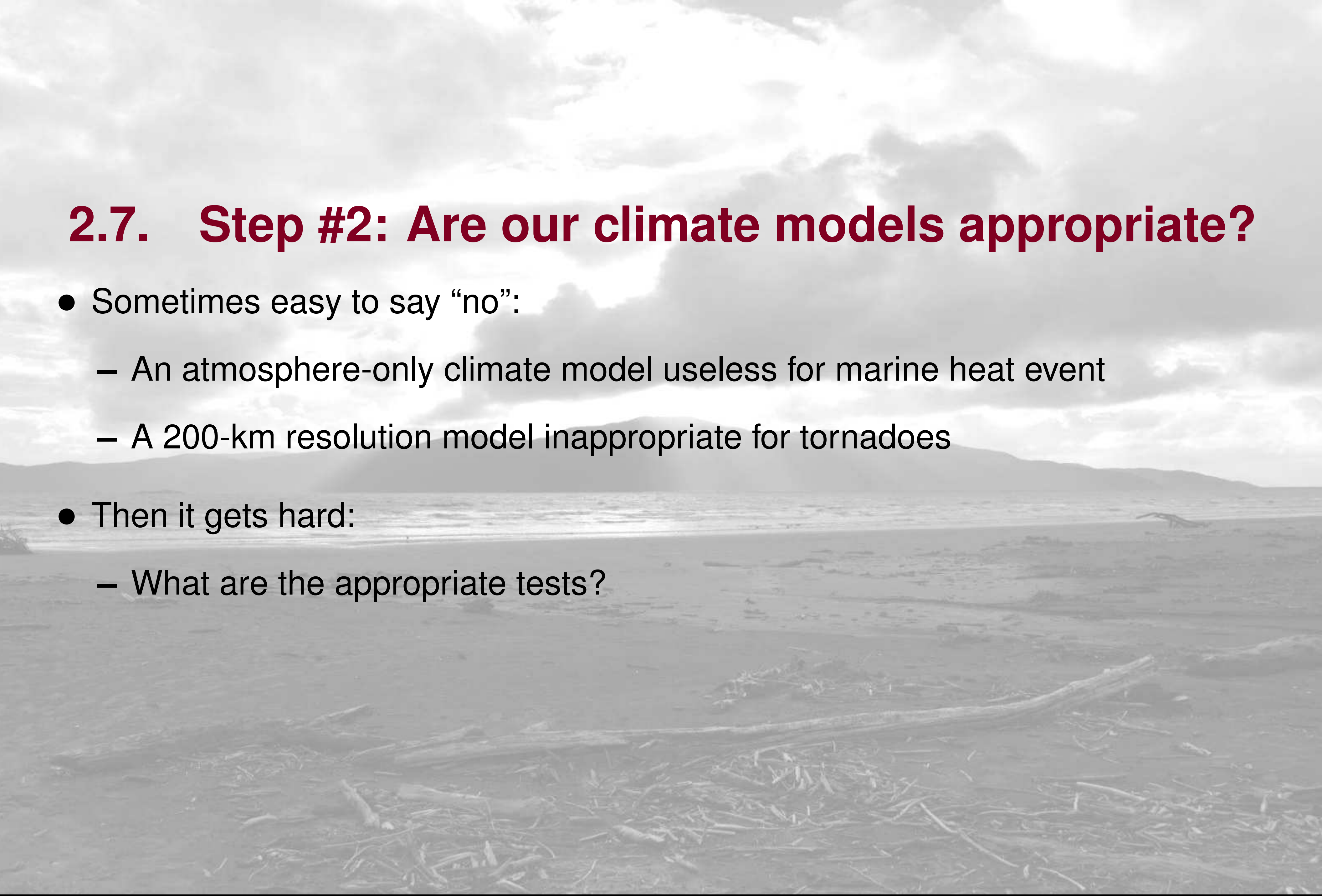
- Are all of these observational products of sufficient quality?

Region definition can matter

- Analysis of unusually wet months in two sets of climate model simulations
- “WRAF” spatial scale is a 2.147Mm^2 region in northwestern United States
- Other spatial scales divide that region into the indicated scale
- Risk ratio (probability ratio) is $\sim$1.3 at large scale
- Ratio ranges from 1/2 to 2 at $\sim$67000km^2 (“1/32 WRAF”) scale
- Also depends on duration and season



Angélil et alii (2018)

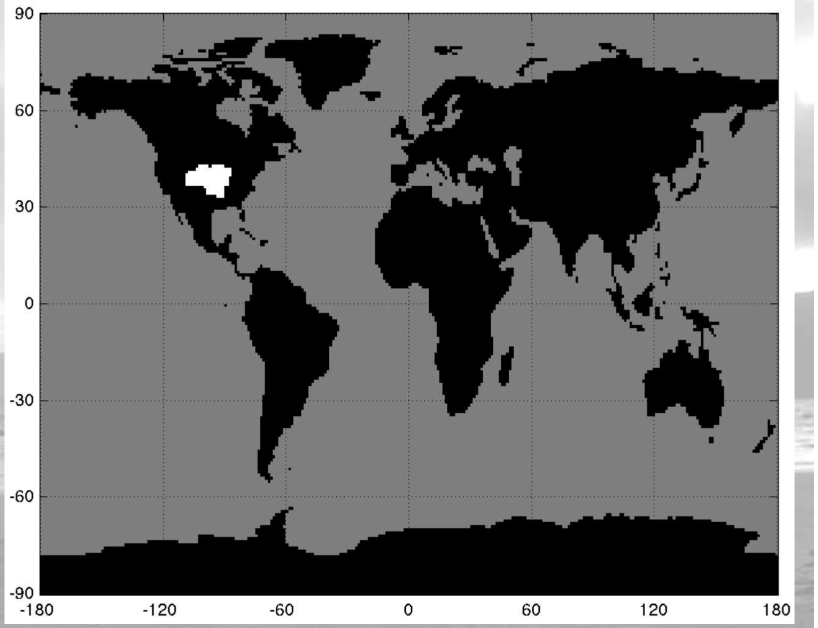


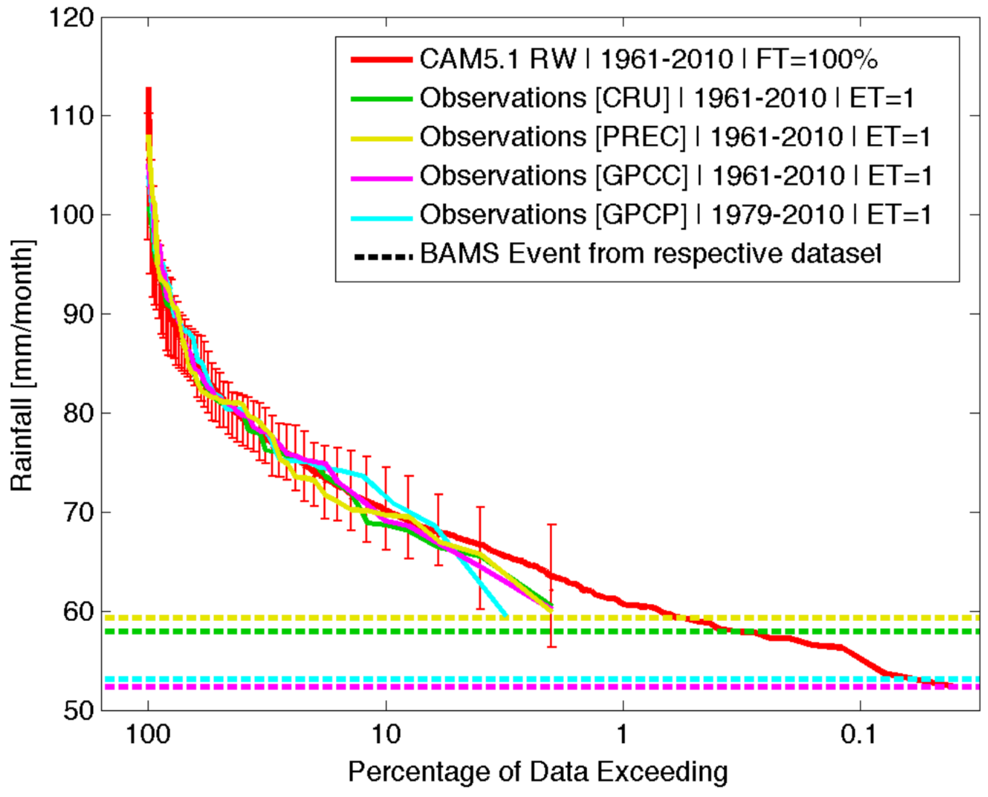
2.7. Step #2: Are our climate models appropriate?

- Sometimes easy to say “no”:
    - An atmosphere-only climate model useless for marine heat event
    - A 200-km resolution model inappropriate for tornadoes
- Then it gets hard:
    - What are the appropriate tests?

Does the model reproduce the climatology?

Precipitation over central U.S. states, March-August 2012

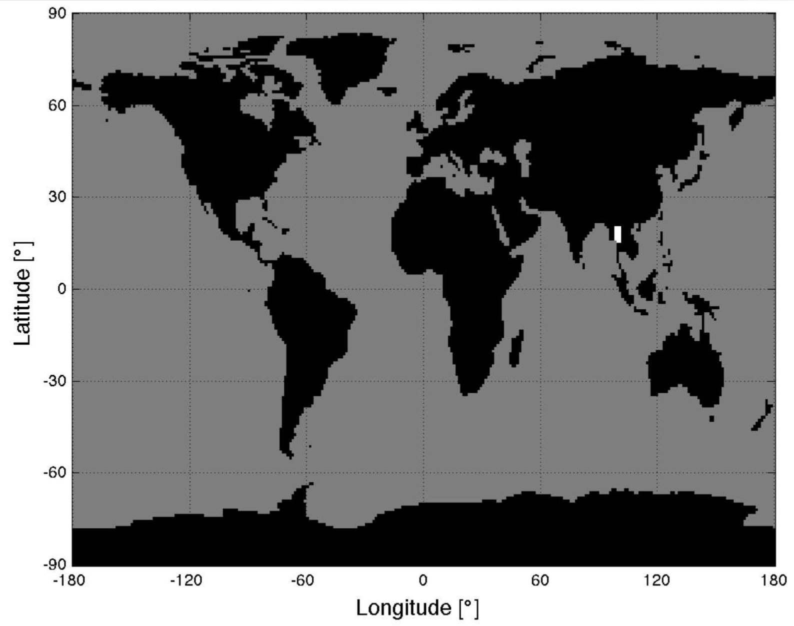


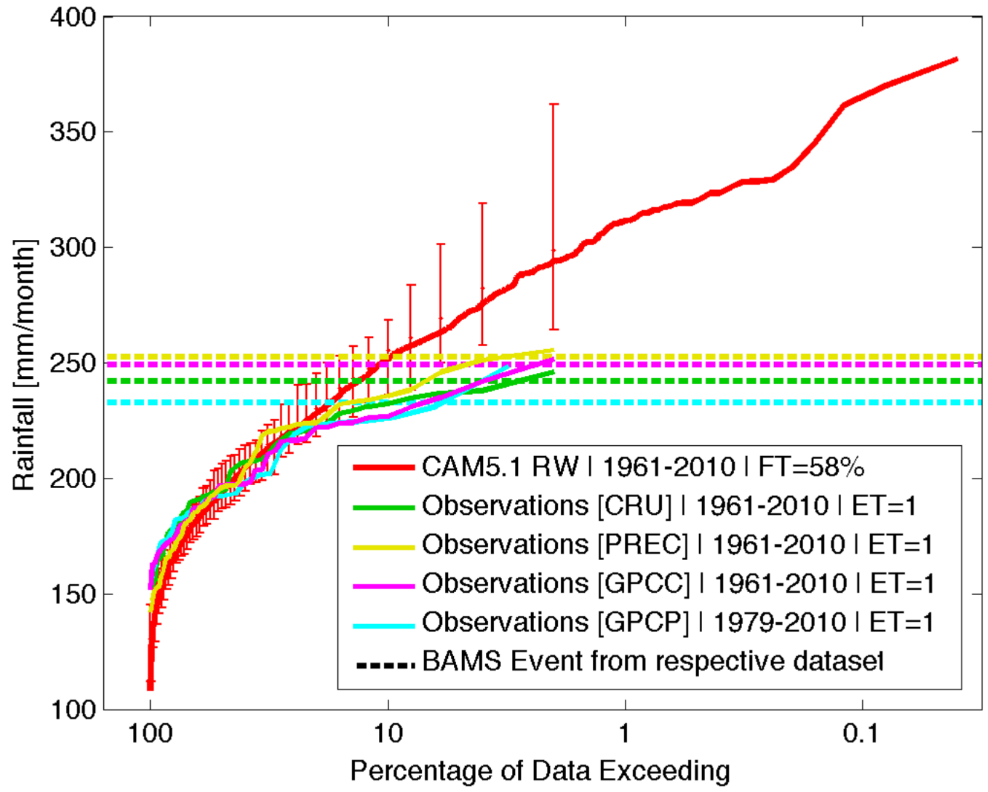


Angélil et alii (2017)

How about for this event?

Precipitation over northern Thailand, July-September 2011

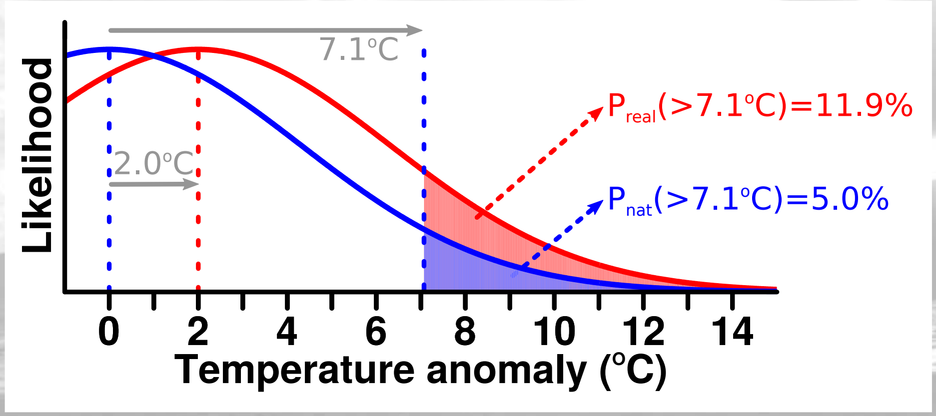




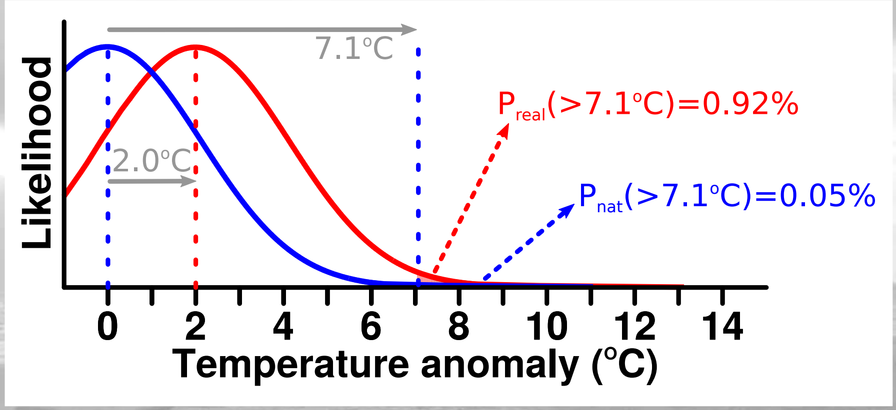
Angélil et alii (2017)

How much does it matter?

Change in probability



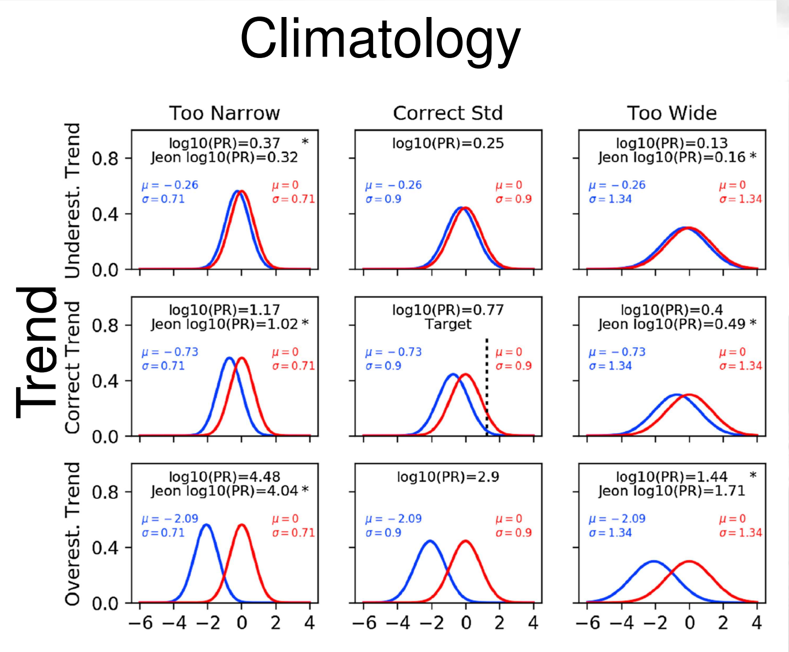
Change with standard deviation halved



- Ratio of probabilities changes from 2.4 to 18!

2.8. Does the model reproduce the forced trend?

1-in-1-year hot event

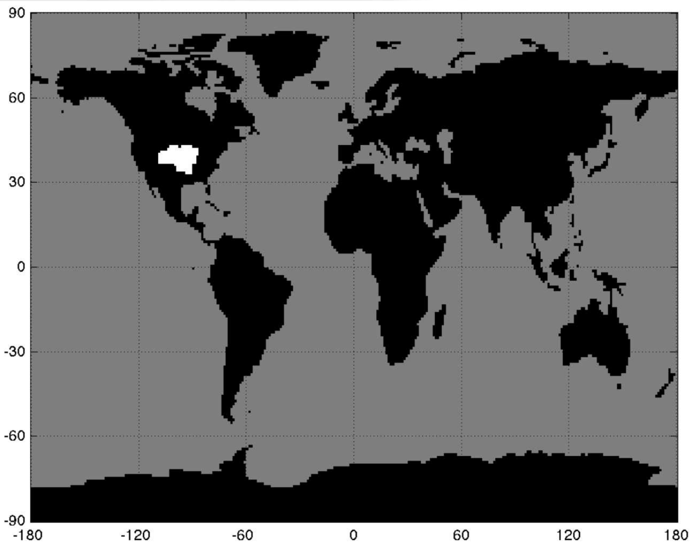


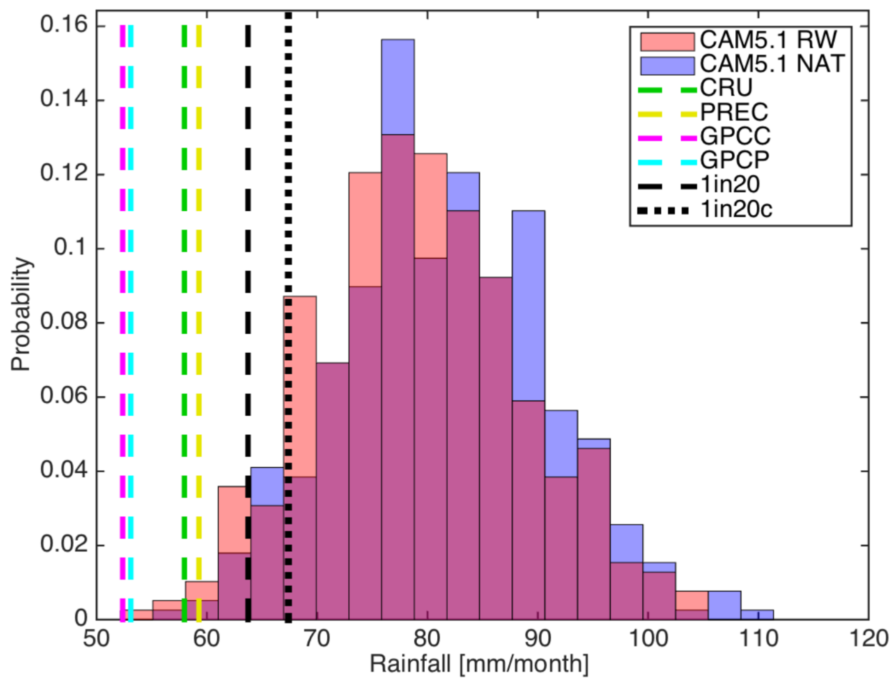
Herger et alii (2018)

- Plot shows range of possible risk ratios given spreads across climate models
  - Range because of trend uncertainty: 20 to 13000
  - Range because of climatology uncertainty: 1.4 to 1100
- *Accuracy in simulating trend may be more important test!*
- For observed climatology we have decades of data to sample daily events
- For the long-term trend we have only one sample!
- D&A of measures of local and rare events is hard...

2.9. Step #3: Compare chance of events

Precipitation over central U.S. states, March-August 2012



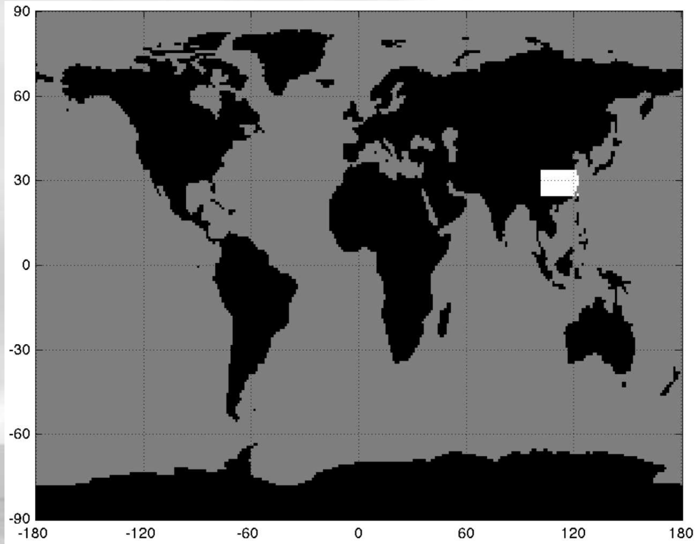


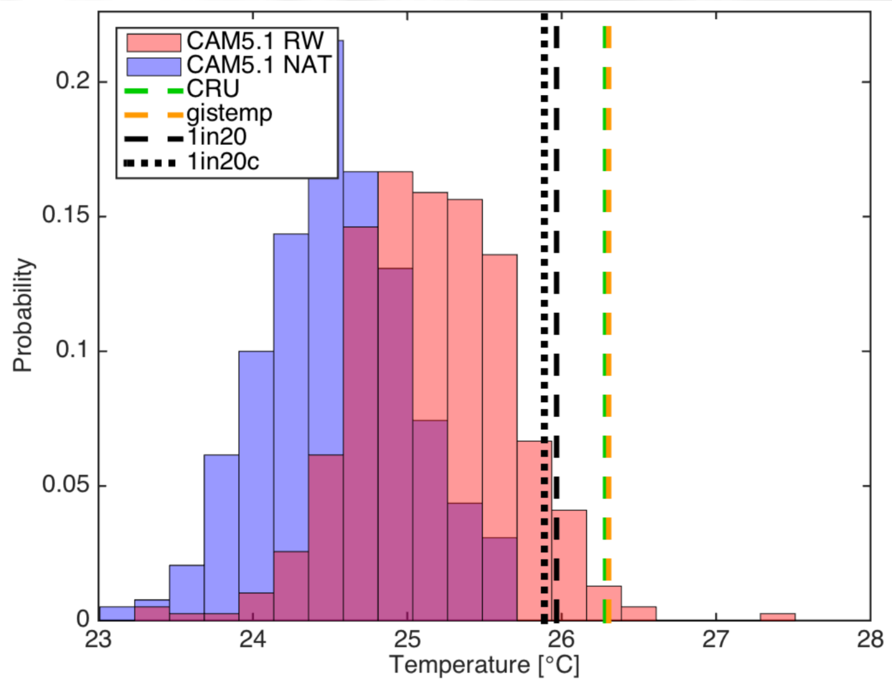
Angélil et alii (2017)

- P_{nat} ranges from 0.11% to 1.03%, depending on observational product
- P_{real} ranges from 0.22% to 1.72%
- So the RR ranges from 1.7 to 2.0

2.10. Another example

Temperature over central eastern China, July-August 2013

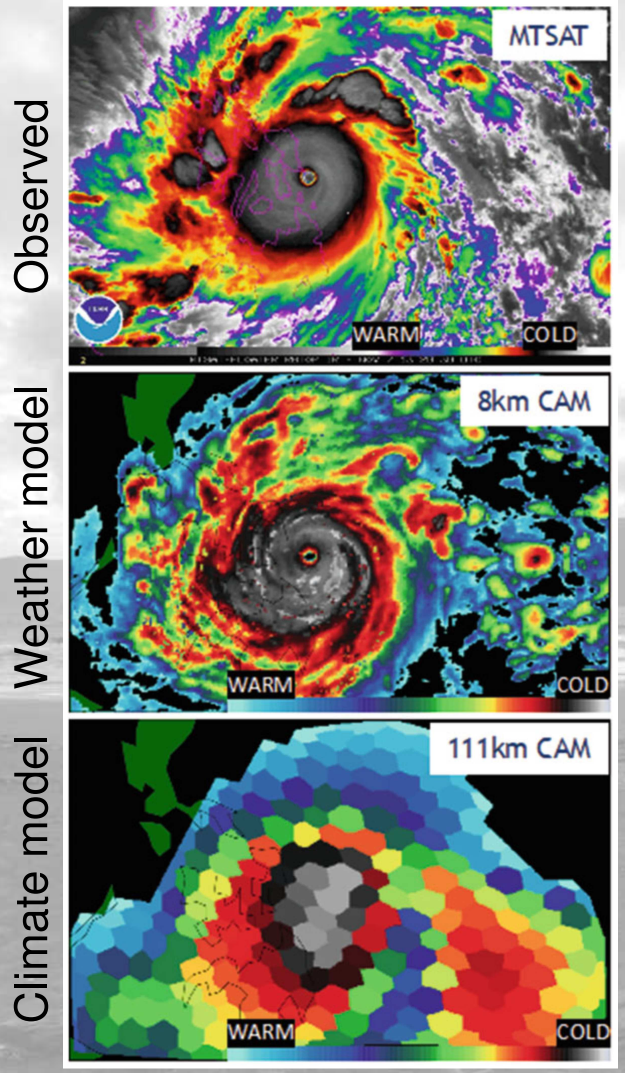




Angélil et alii (2017)

- P_{nat} ranges from 0.01% for both observational products
- P_{real} ranges from 1.06% to 1.18%
- So the RR ranges from 100 to 120

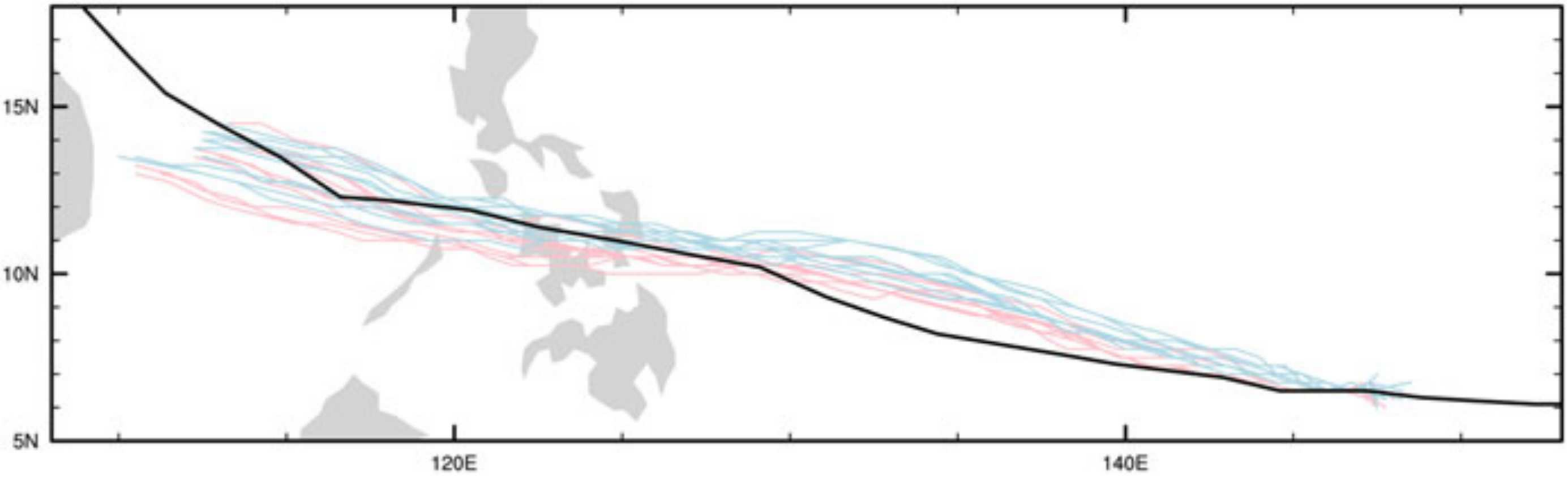
2.11. Events that today’s climate models cannot do



Wehner et alii (2019)

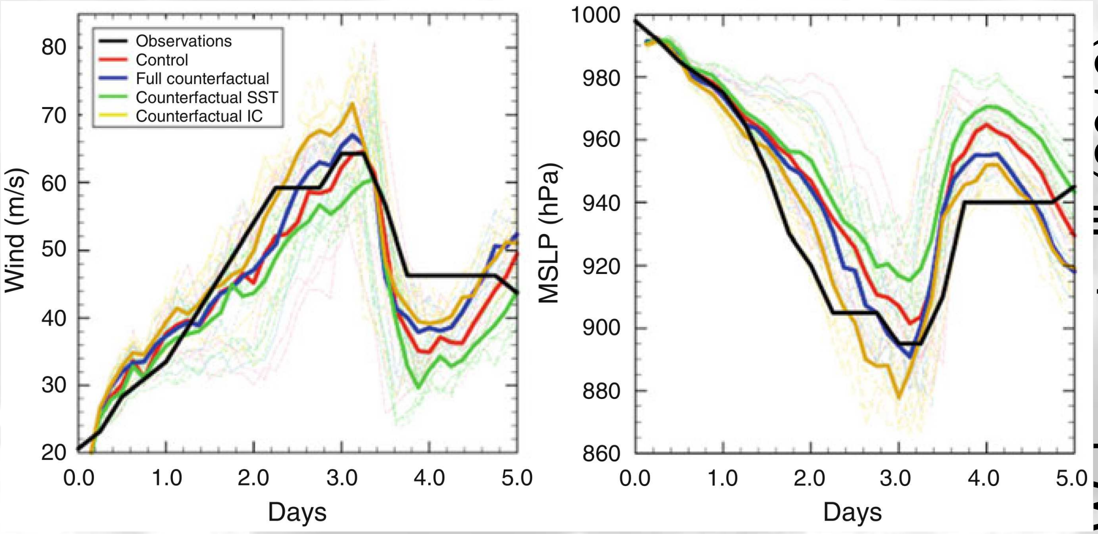
- Tropical cyclones cannot be properly represented using models typically used for climate change study (about 100km grid resolution or coarser)
- They can be nicely simulated by when these models are run at higher resolution (e.g. 8km)
  - But then too expensive to run over many years
  - Instead, let’s use them to make forecasts (but afterward, so “hindcasts”) and “forecasts that might have been without human interference”

2.12. Hindcasts of Typhoon Haiyan (Yolanda)



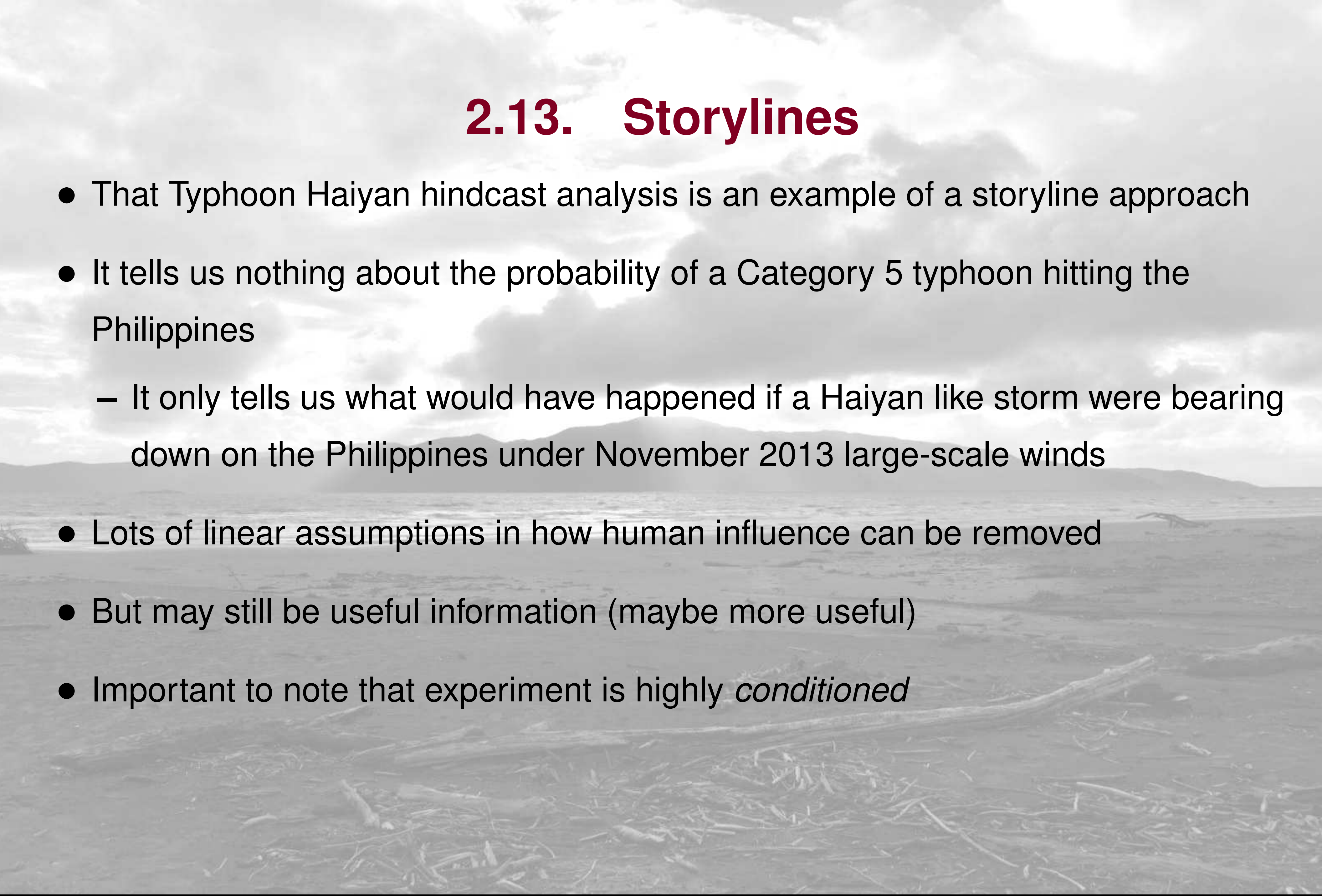
Wehner et alii (2019)

- Red: hindcasts under observed conditions
- Blue: hindcasts under naturalised observed conditions (i.e. with human influence removed)
- Important: The tracks are pretty much the same, so we are looking at the same storm in both scenarios!



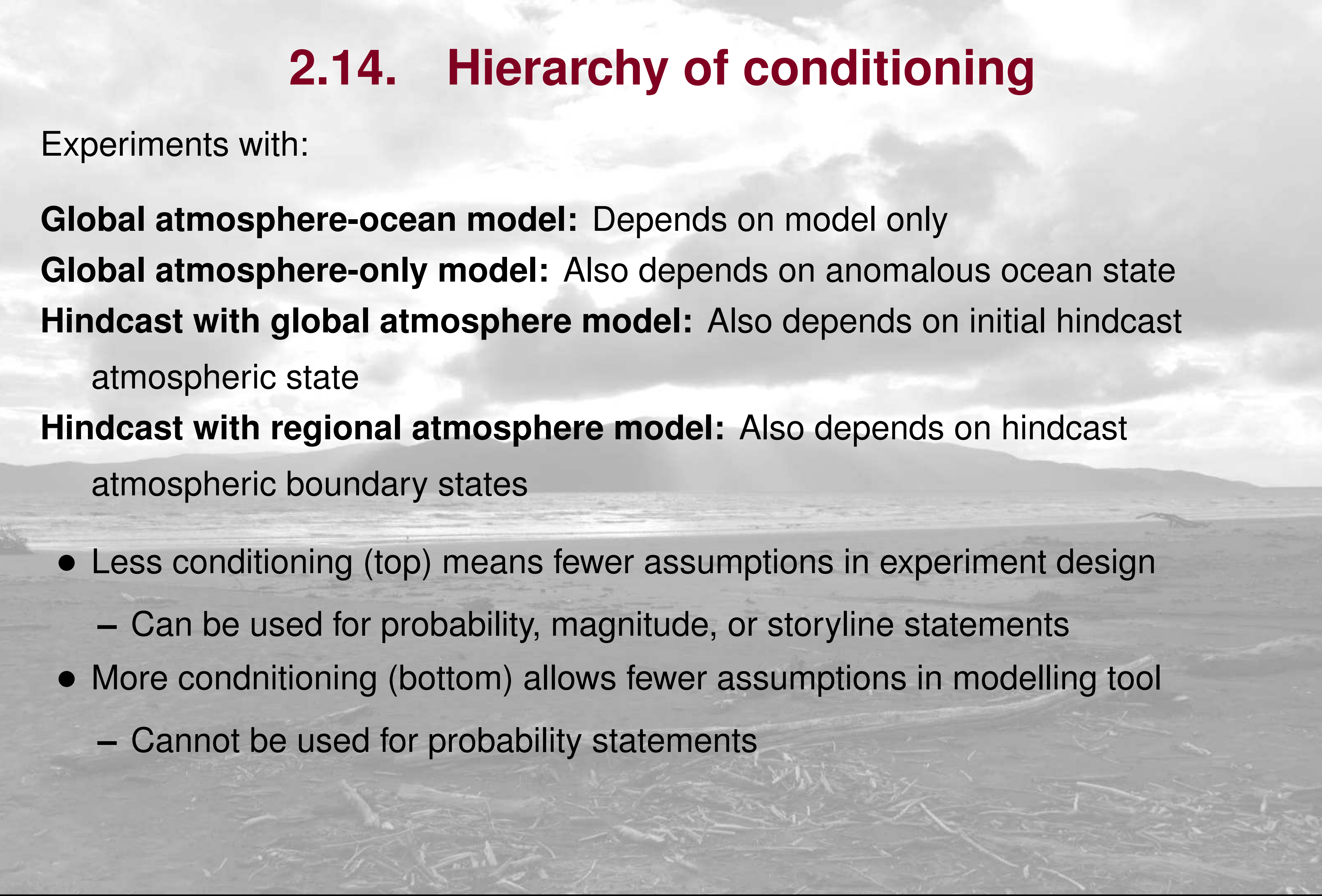
Wehner et alii (2019)

- Red: hindcasts under observed conditions
- Blue: hindcasts under naturalised observed conditions (i.e. with human influence removed)
- According to this experiment, human influenced *decreased* wind speed and central pressure anomaly
- Effect of anthropogenic ocean warming (green) and atmospheric warming and wetting (green) oppose each other



2.13. Storylines

- That Typhoon Haiyan hindcast analysis is an example of a storyline approach
- It tells us nothing about the probability of a Category 5 typhoon hitting the Philippines
  - It only tells us what would have happened if a Haiyan like storm were bearing down on the Philippines under November 2013 large-scale winds
- Lots of linear assumptions in how human influence can be removed
- But may still be useful information (maybe more useful)
- Important to note that experiment is highly *conditioned*



2.14. Hierarchy of conditioning

Experiments with:

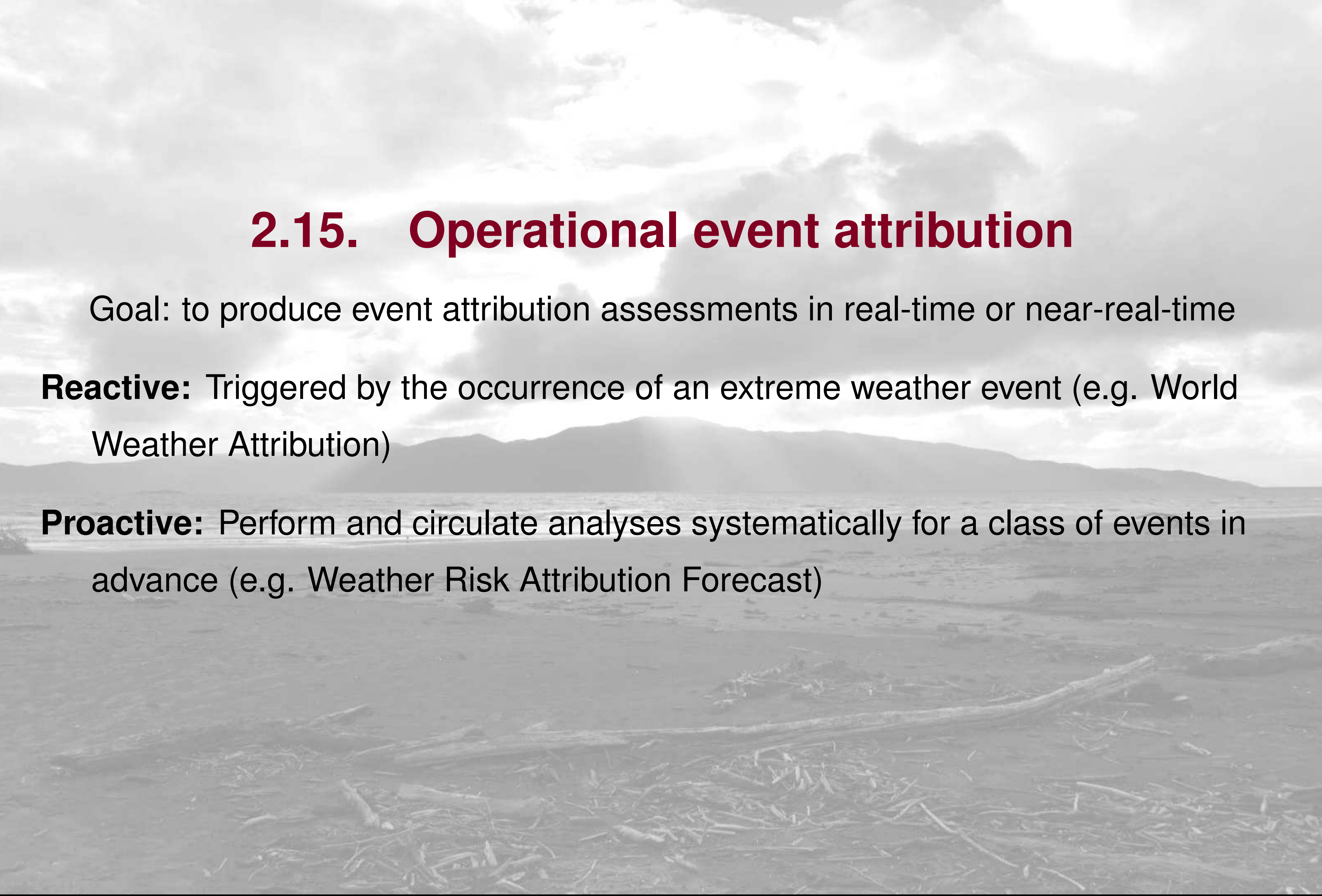
Global atmosphere-ocean model: Depends on model only

Global atmosphere-only model: Also depends on anomalous ocean state

Hindcast with global atmosphere model: Also depends on initial hindcast atmospheric state

Hindcast with regional atmosphere model: Also depends on hindcast atmospheric boundary states

- Less conditioning (top) means fewer assumptions in experiment design
  - Can be used for probability, magnitude, or storyline statements
- More condnitioning (bottom) allows fewer assumptions in modelling tool
  - Cannot be used for probability statements



2.15. Operational event attribution

Goal: to produce event attribution assessments in real-time or near-real-time

Reactive: Triggered by the occurrence of an extreme weather event (e.g. World Weather Attribution)

Proactive: Perform and circulate analyses systematically for a class of events in advance (e.g. Weather Risk Attribution Forecast)

Dáithí Stone (dastone@runbox.com)

2.16. Operational event attribution in action

- This occurred in the last week of June 2019
- Analysis posted on 2 July 2019

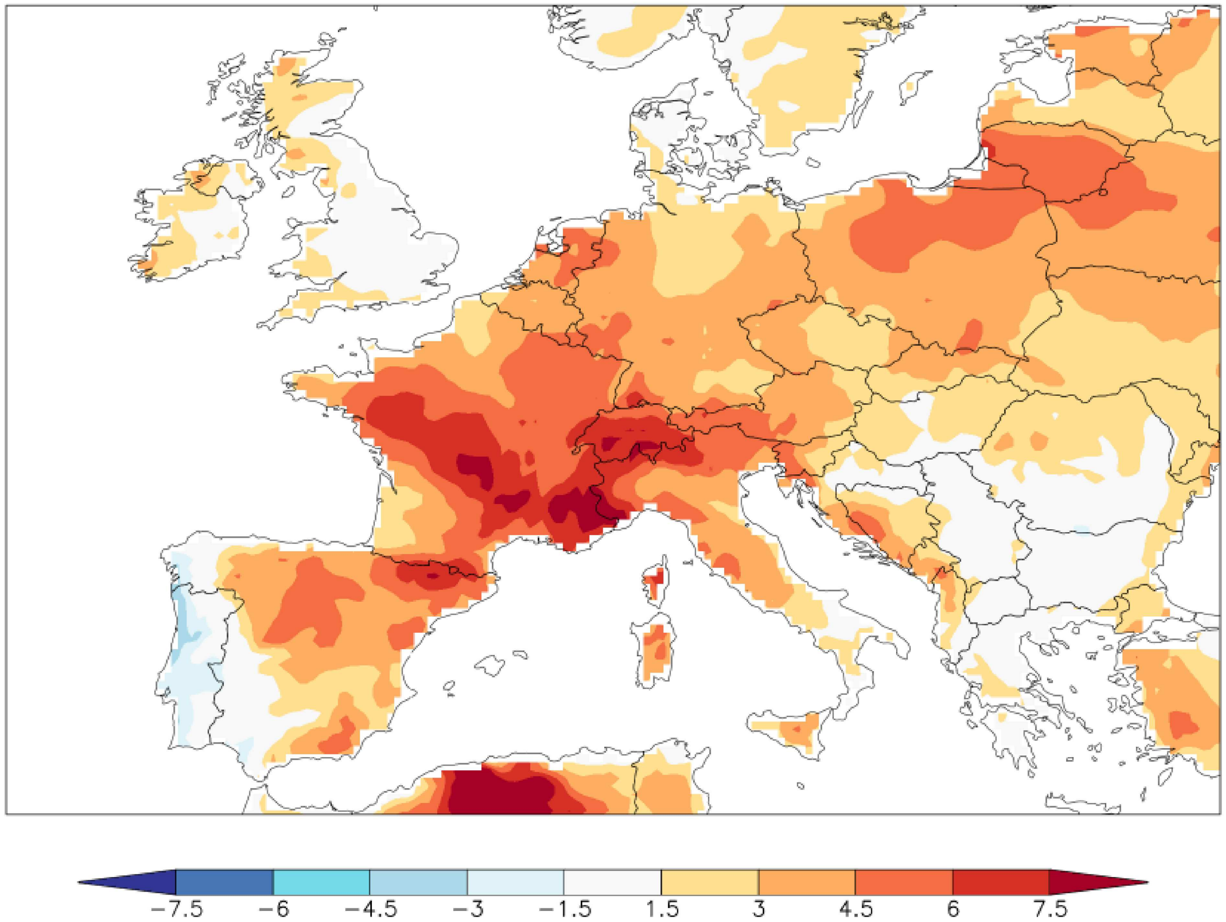


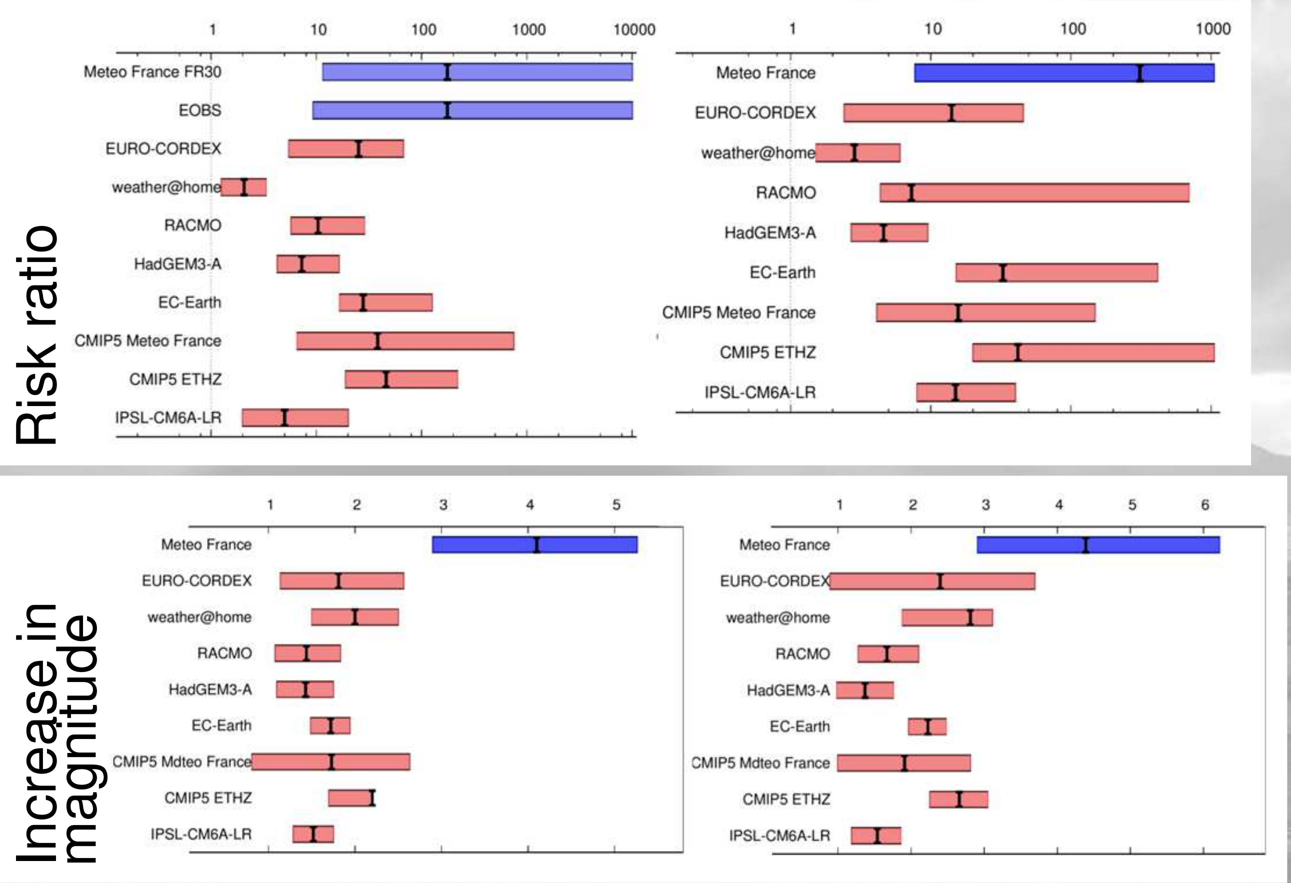
Figure 1a: The highest 3-day daily mean temperature in June 2019 compared to the highest values in 1981–2010 Source: E-OBS (preliminary data)

World Weather Attribution (van Oldenborgh et alii 2019)

Assessment for France and Toulouse, late June 2019

Mainland France

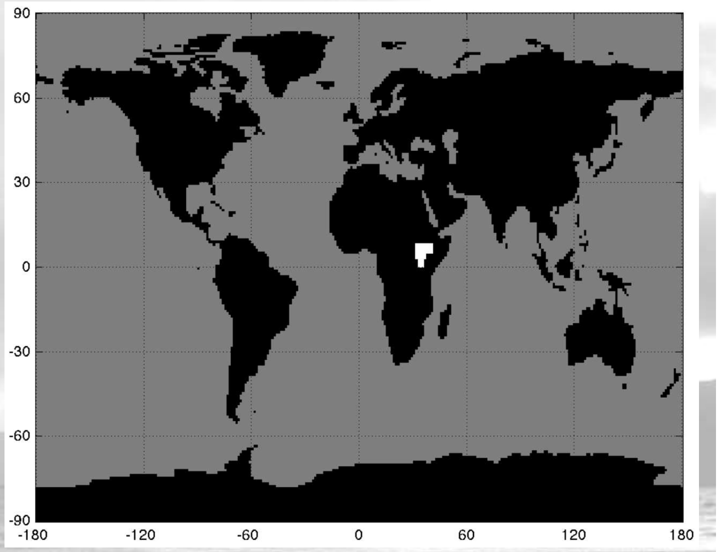
Toulouse

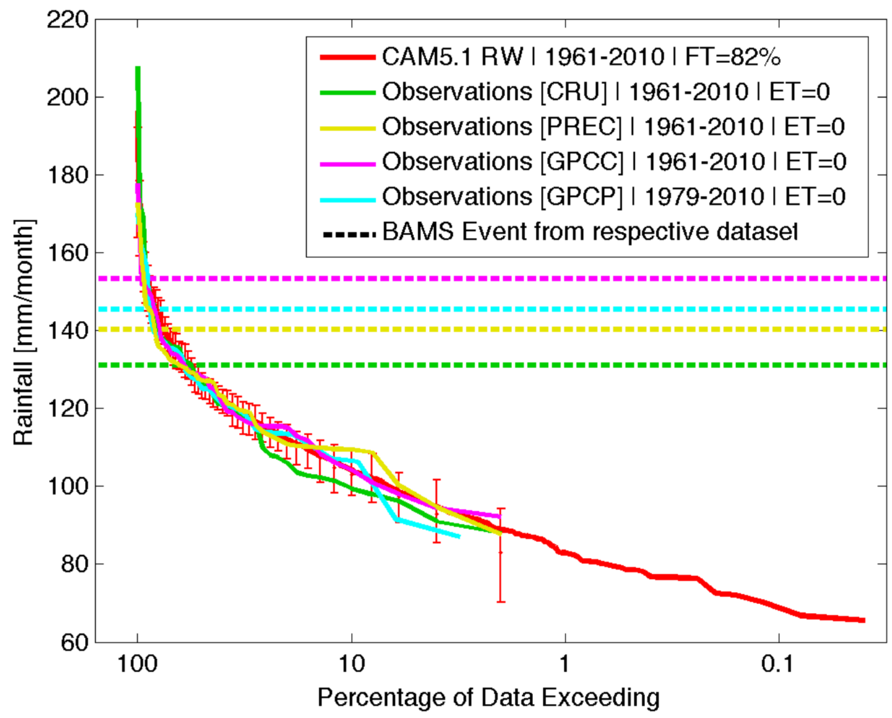


World Weather Attribution
(van Oldenborgh et alii 2019)

2.17. Challenges in working in (near-)real-time

Precipitation over East Africa, June-September 2011



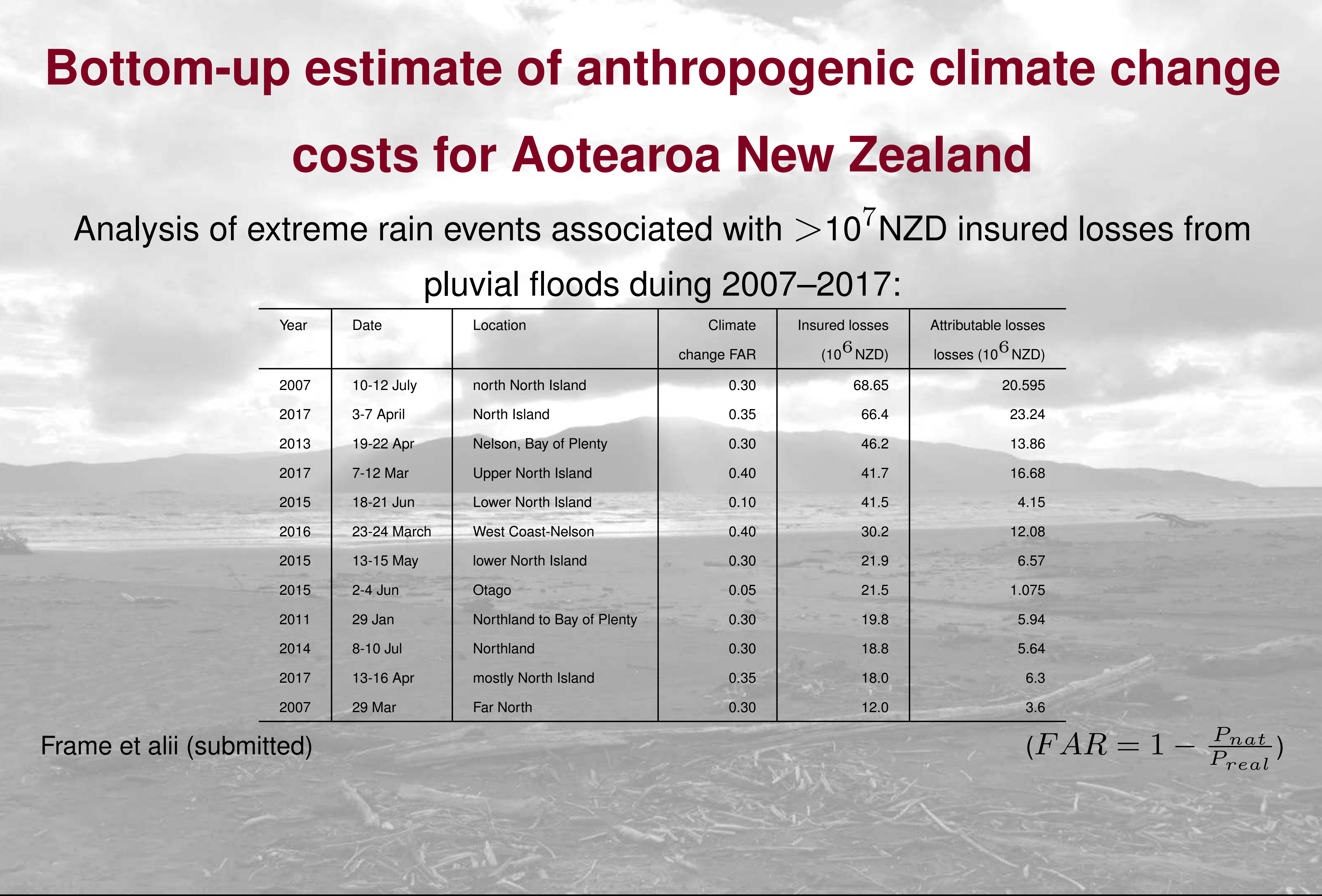


Angélil et alii (2017)

- An event attribution study was published on this “drought”!
- Error in comparing prototype new operational monitoring product against traditional historical products in monitoring-poor region

2.18. Event attribution as a bottom-up costing method

- Estimates of the cost of climate change tend to come from “top-down” methods
  - Using integrated assessment models to simulate climate, natural, and human systems
- Top-down methods are expensive and are only feasible with coarse approximations of all of the various processes
  - They do not produce local extremes
- But local extremes are the most costly part of current climate risk!
  - For instance, tropical cyclones
- Can we estimate climate change costs for extreme weather events?



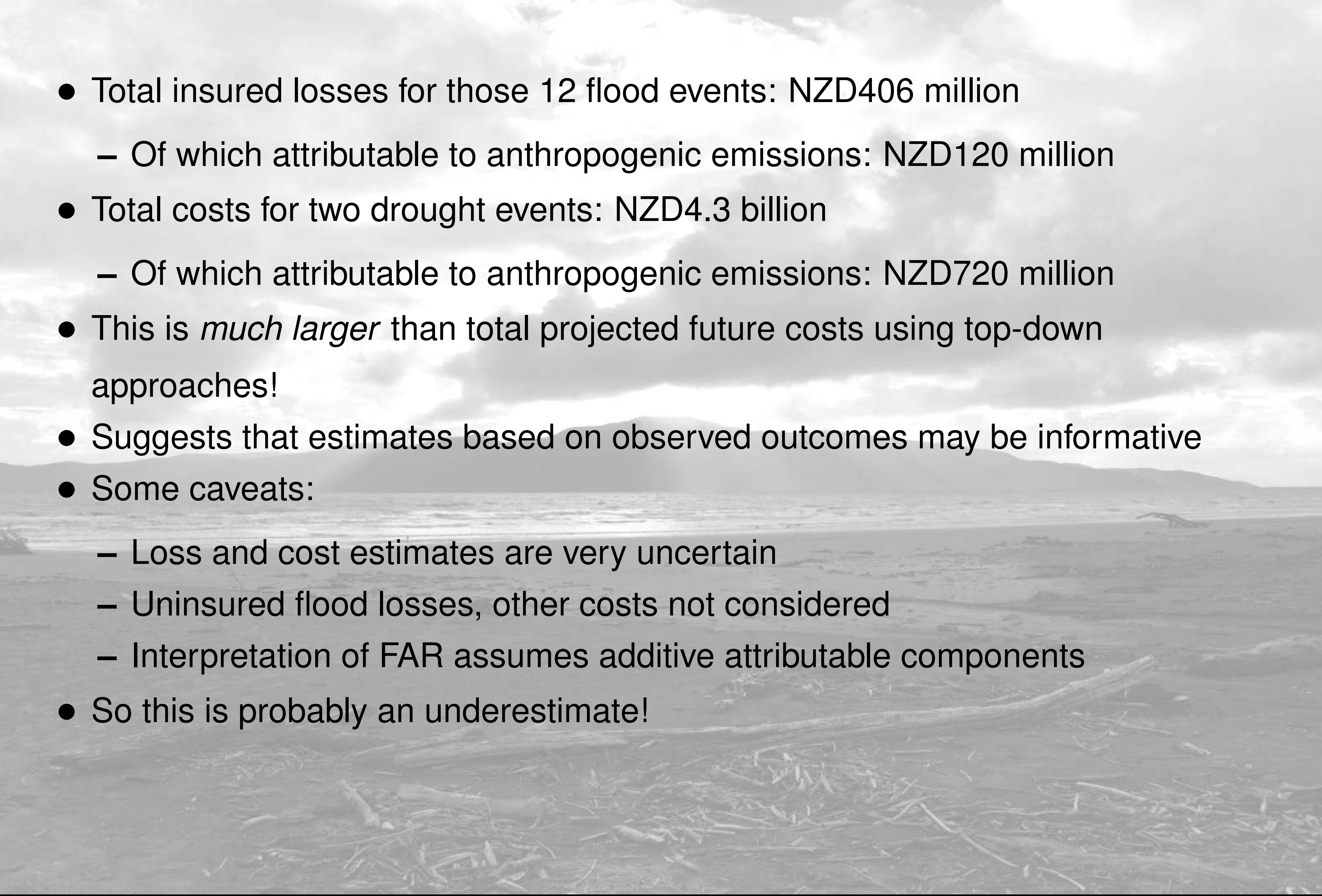
Bottom-up estimate of anthropogenic climate change costs for Aotearoa New Zealand

Analysis of extreme rain events associated with $>10^7$NZD insured losses from pluvial floods duing 2007–2017:

Year	Date	Location	Climate change FAR	Insured losses (10^6NZD)	Attributable losses losses (10^6NZD)
2007	10-12 July	north North Island	0.30	68.65	20.595
2017	3-7 April	North Island	0.35	66.4	23.24
2013	19-22 Apr	Nelson, Bay of Plenty	0.30	46.2	13.86
2017	7-12 Mar	Upper North Island	0.40	41.7	16.68
2015	18-21 Jun	Lower North Island	0.10	41.5	4.15
2016	23-24 March	West Coast-Nelson	0.40	30.2	12.08
2015	13-15 May	lower North Island	0.30	21.9	6.57
2015	2-4 Jun	Otago	0.05	21.5	1.075
2011	29 Jan	Northland to Bay of Plenty	0.30	19.8	5.94
2014	8-10 Jul	Northland	0.30	18.8	5.64
2017	13-16 Apr	mostly North Island	0.35	18.0	6.3
2007	29 Mar	Far North	0.30	12.0	3.6

Frame et alii (submitted)

$$(FAR = 1 - \frac{P_{nat}}{P_{real}})$$



- Total insured losses for those 12 flood events: NZD406 million
  - Of which attributable to anthropogenic emissions: NZD120 million
- Total costs for two drought events: NZD4.3 billion
  - Of which attributable to anthropogenic emissions: NZD720 million
- This is *much larger* than total projected future costs using top-down approaches!
- Suggests that estimates based on observed outcomes may be informative
- Some caveats:
  - Loss and cost estimates are very uncertain
  - Uninsured flood losses, other costs not considered
  - Interpretation of FAR assumes additive attributable components
- So this is probably an underestimate!

2.19. What can we say about change in total risk?

$$Risk = \Sigma_{h=Hazard}\left(Probability[h] \cdot Exposure[h] \cdot Vulnerability[h]\right)$$

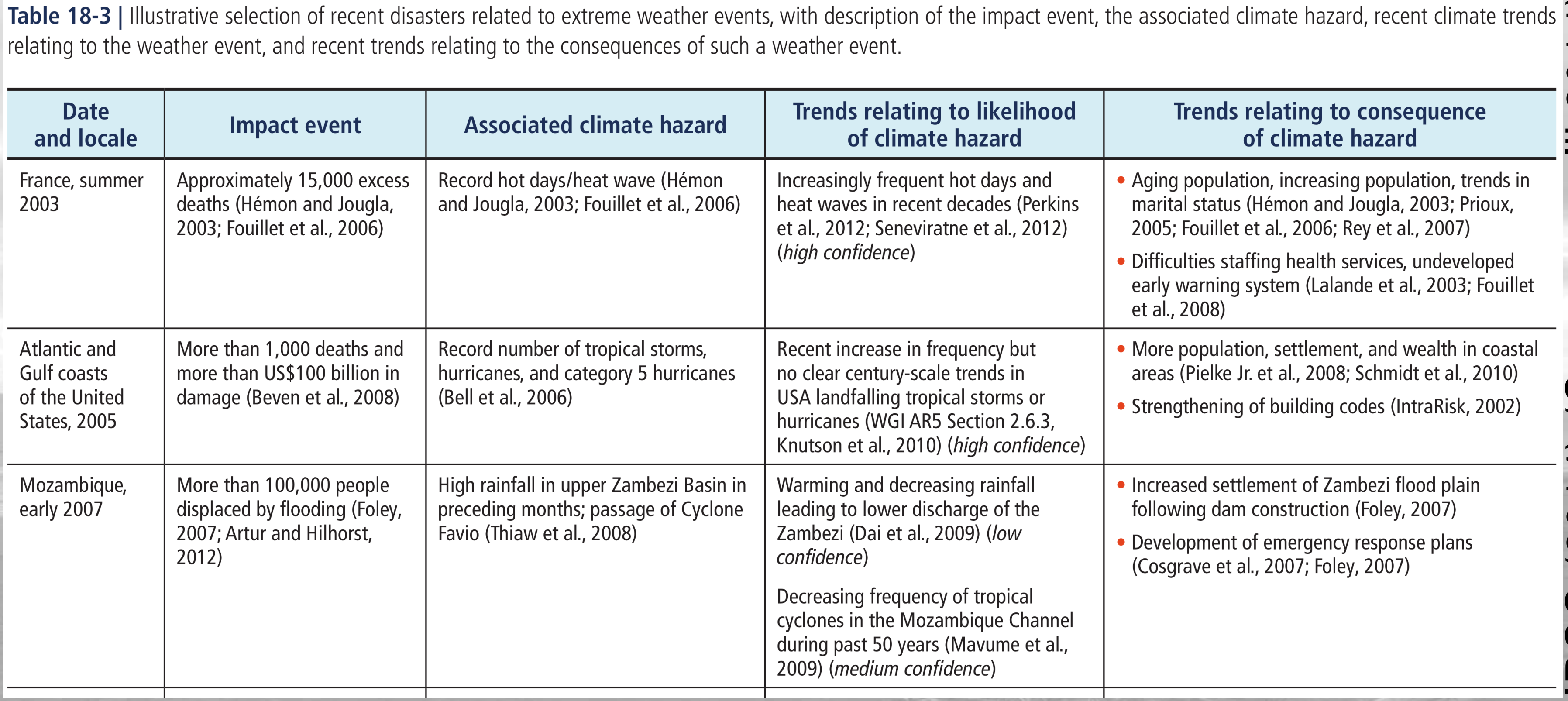


Table 18-3 | Illustrative selection of recent disasters related to extreme weather events, with description of the impact event, the associated climate hazard, recent climate trends relating to the weather event, and recent trends relating to the consequences of such a weather event.

Date and locale	Impact event	Associated climate hazard	Trends relating to likelihood of climate hazard	Trends relating to consequence of climate hazard
France, summer 2003	Approximately 15,000 excess deaths (Hémon and Jougla, 2003; Fouillet et al., 2006)	Record hot days/heat wave (Hémon and Jougla, 2003; Fouillet et al., 2006)	Increasingly frequent hot days and heat waves in recent decades (Perkins et al., 2012; Seneviratne et al., 2012) (*high confidence*)	• Aging population, increasing population, trends in marital status (Hémon and Jougla, 2003; Prioux, 2005; Fouillet et al., 2006; Rey et al., 2007) • Difficulties staffing health services, undeveloped early warning system (Lalande et al., 2003; Fouillet et al., 2008)
Atlantic and Gulf coasts of the United States, 2005	More than 1,000 deaths and more than US$100 billion in damage (Beven et al., 2008)	Record number of tropical storms, hurricanes, and category 5 hurricanes (Bell et al., 2006)	Recent increase in frequency but no clear century-scale trends in USA landfalling tropical storms or hurricanes (WGI AR5 Section 2.6.3, Knutson et al., 2010) (*high confidence*)	• More population, settlement, and wealth in coastal areas (Pielke Jr. et al., 2008; Schmidt et al., 2010) • Strengthening of building codes (IntraRisk, 2002)
Mozambique, early 2007	More than 100,000 people displaced by flooding (Foley, 2007; Artur and Hilhorst, 2012)	High rainfall in upper Zambezi Basin in preceding months; passage of Cyclone Favio (Thiaw et al., 2008)	Warming and decreasing rainfall leading to lower discharge of the Zambezi (Dai et al., 2009) (*low confidence*) Decreasing frequency of tropical cyclones in the Mozambique Channel during past 50 years (Mavume et al., 2009) (*medium confidence*)	• Increased settlement of Zambezi flood plain following dam construction (Foley, 2007) • Development of emergency response plans (Cosgrave et al., 2007; Foley, 2007)

IPCC (2014) (Cramer et alii 2014)

- We need to consider much more than climate!

2.20. Main messages

- We can say something about the role that our emissions (or land use/cover change, etc.) have had on a particular event, at least in theory.
- For some events we may be able to address them in their entirety.
- For some events we may only be able to address some properties at the moment, but not others.
- There are different ways of thinking of causality and inferring causality.
  - *They may lead to apparently contradictory conclusions!*
- “Event attribution” is distinct from “detection and attribution”.
  - Event attribution analyses can consider events far in the future (e.g. 2100).
  - D&A can only every analyse the past.
- Usage of D&A information in event attribution studies is limited so far.