Severe Weather Impacts of Climate Change
From hot air to environmental injustice

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CSASP
July 24, 2023

US DOE Policy 411.2A

SUBJECT: SCIENTIFIC INTEGRITY

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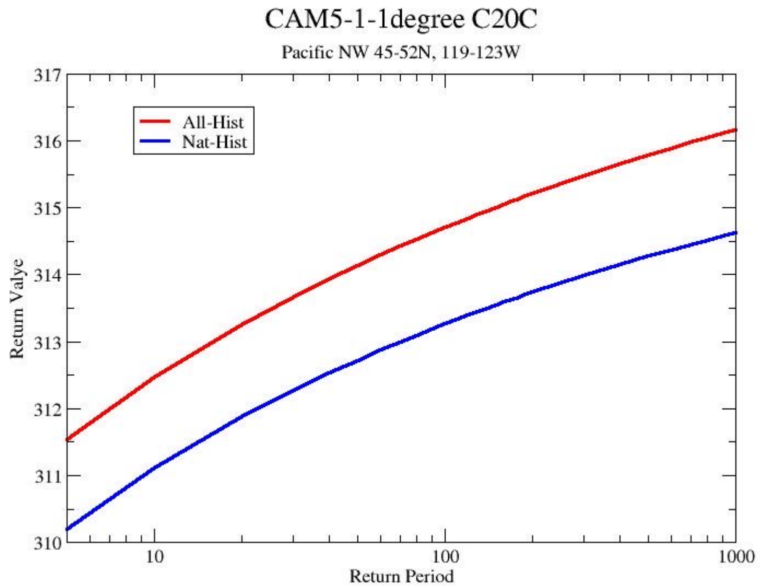
The typical weather event attribution questions:

1. **“How has the probability of this event changed because of climate change?”**

Or

2. **“How did climate change affect the magnitude of this event?”**



These are two sides of the same question.

← 2021 Pacific Northwest heatwave.
Red: World with climate change
Blue: World without climate change
1) Fix the magnitude
2) Fix the probability.

Public attention often focuses on the first question.

30 times more likely sounds bigger than a 2^{o} increase.

Impact questions are slightly different

- How much did climate change cost in this event?
- How many people died because of climate change?

Or more personally,

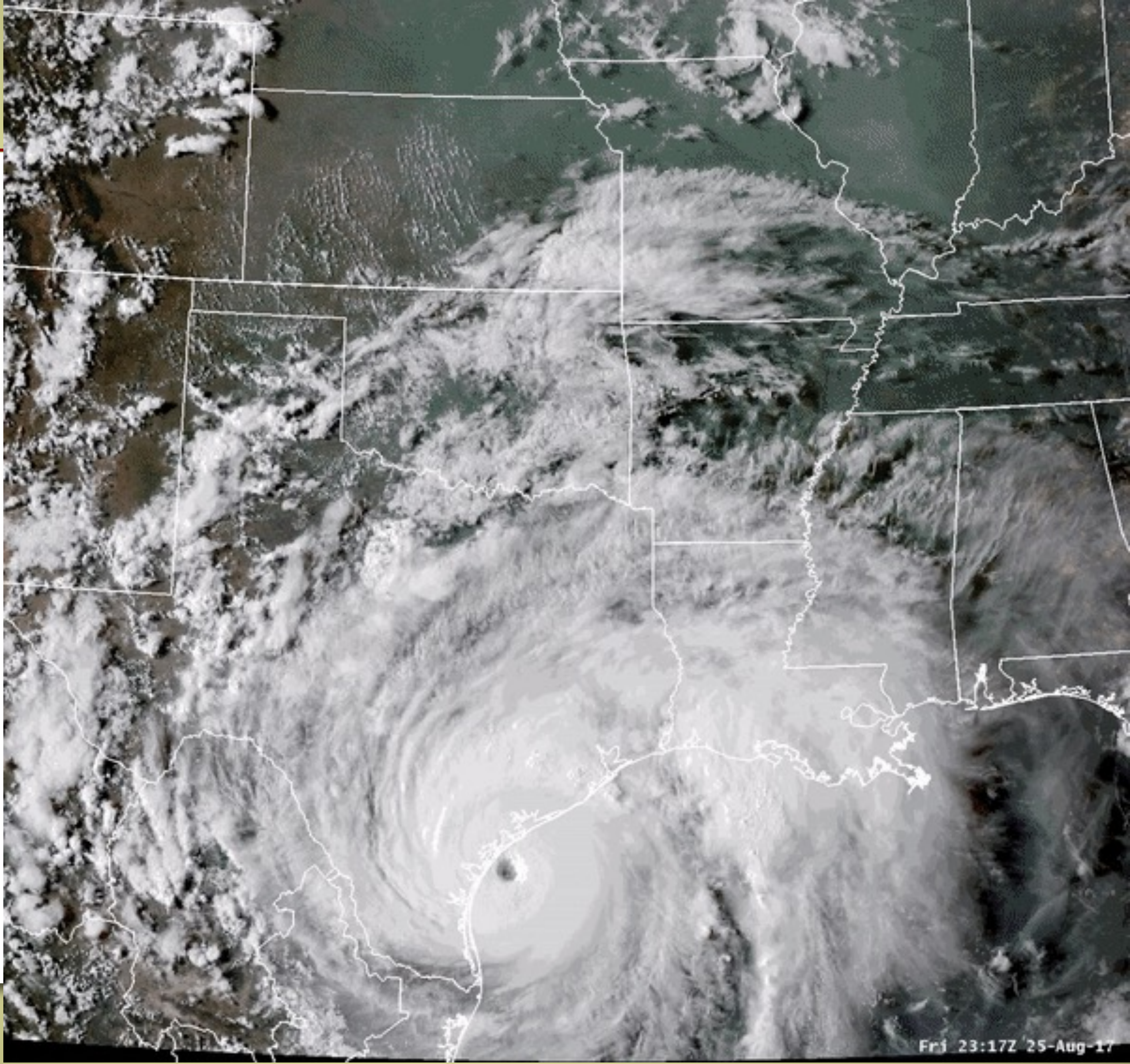
- Did climate change flood my house?
- Did climate change kill my loved one?

These may or may not be tractable questions.

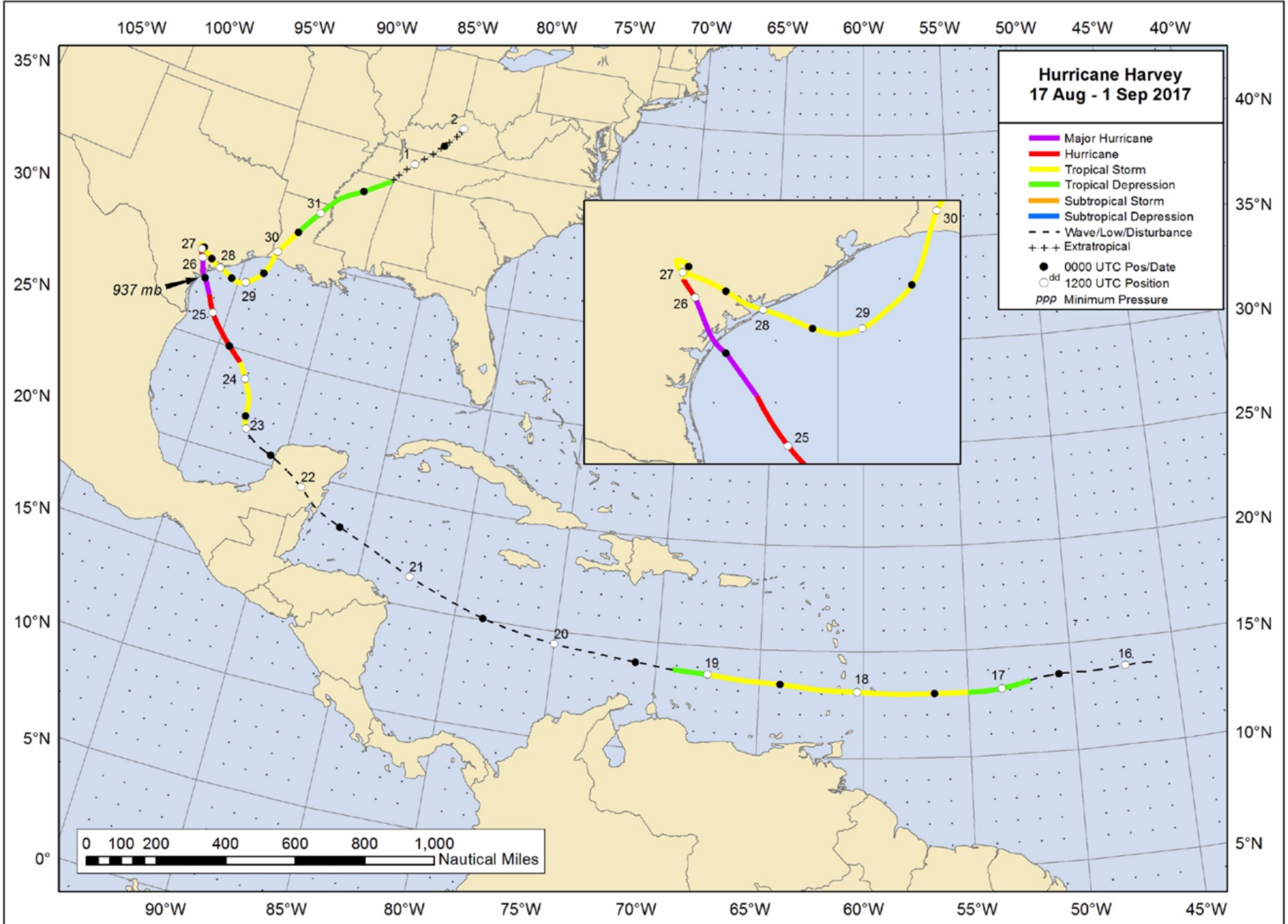
Fundamentally, they are linked to the change in magnitude question. (*Mostly*).

Harvey

August 2017



NOAA



National Hurricane Center

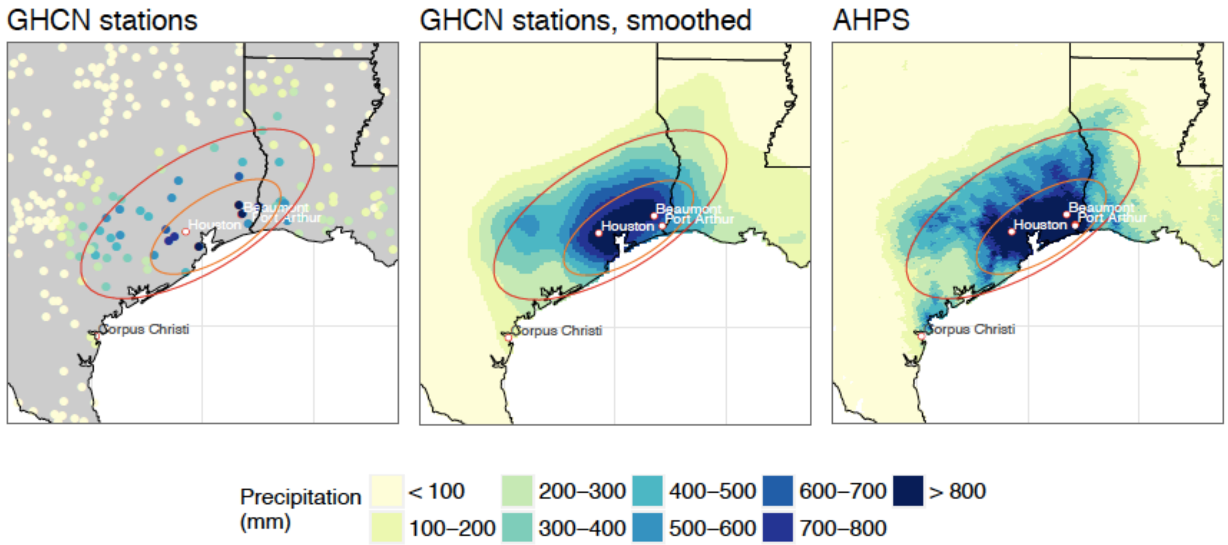
U.S. DEPARTMENT OF ENERGY | Office of Science

Global warming to rain

- Hurricane Harvey produced copious amounts of precipitation
- 3 independent groups analyzed the attributable precipitation increase due to anthropogenic global warming.
- **All made best estimates exceeding that expected by Clausius-Clapeyron scaling (~7% from 1C of warming in the Gulf).**
  - 3 different modeling methods
  - 3 different observational data sets

Risser & Wehner: 24%
van Oldenborg et al: 16%
Wang et al: 20%

Average ~19%
Upper bound 38%
Lower bound 7%



An aside: Extreme Event Attribution is causal inference.

Two complementary philosophies

1. Design ensembles of climate model simulations tailored to event attribution.
   - Actual world vs counterfactual world without human changes to the atmosphere. A direct interference.
   - Pearl causal inference.

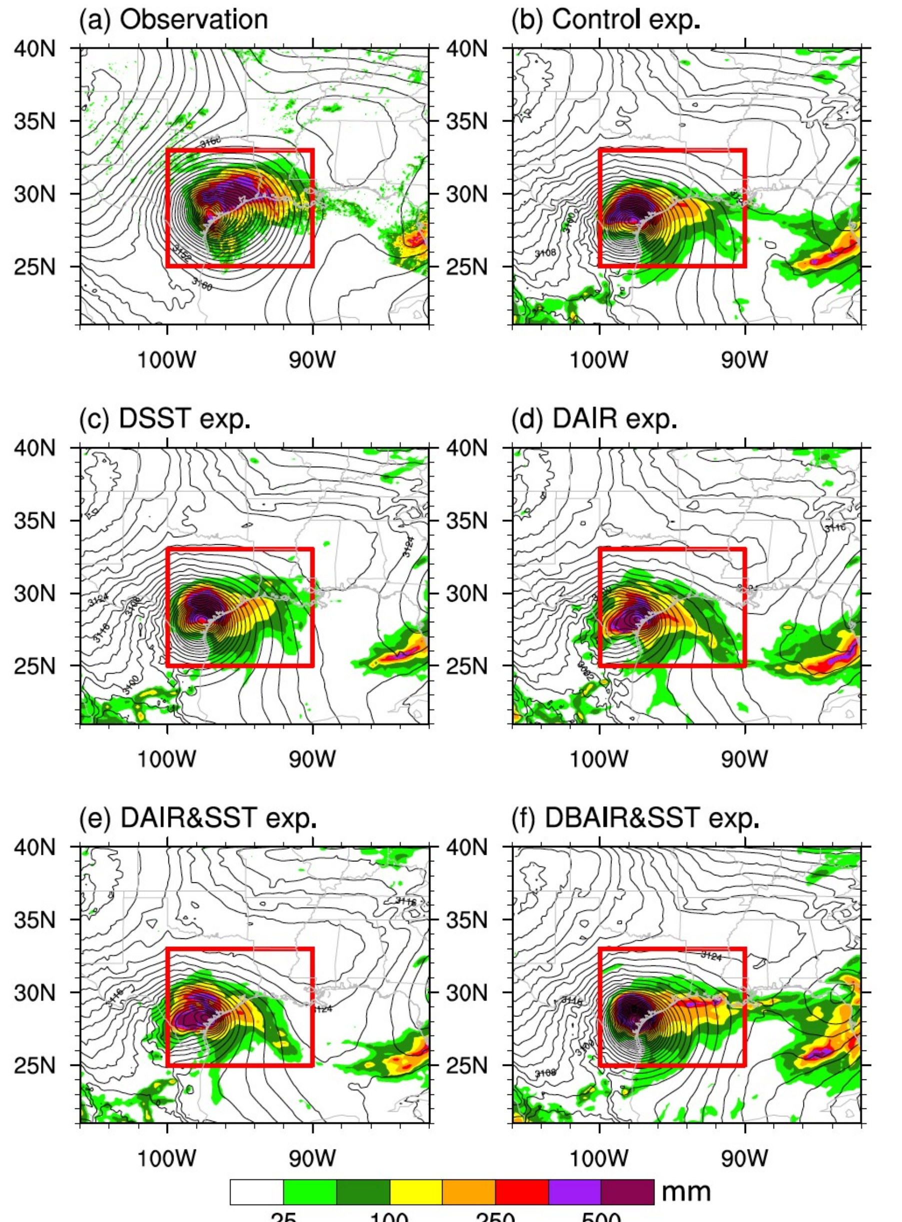
Prof. Judea Pearl, UCLA

2. Analyze observed trends with a statistical model.
   - Postulate a plausible cause but beware of hidden covariates.
   - Granger causal inference.

Sir Clive Granger (1934-2009)

Pearl Causal inference via a storyline

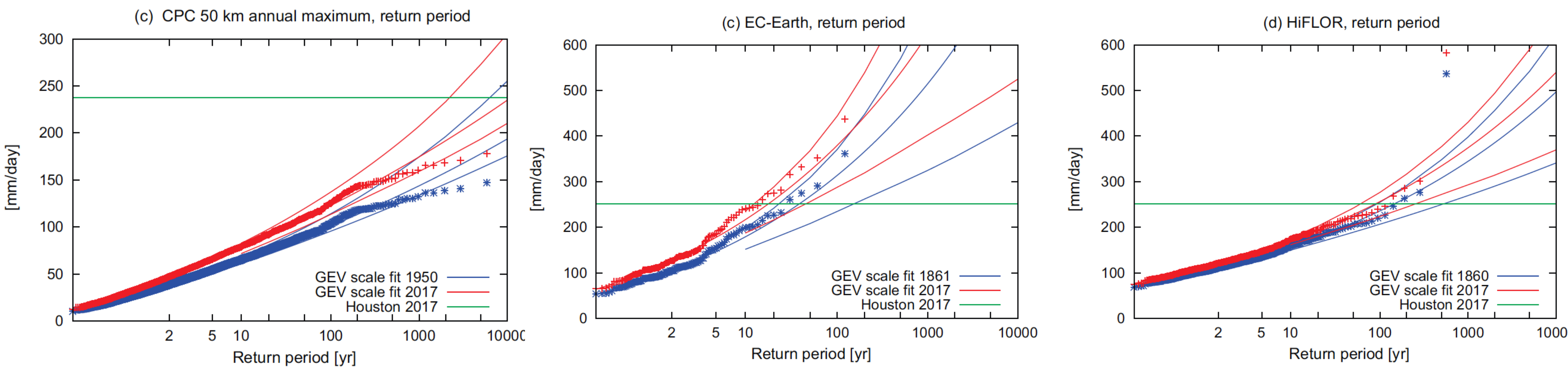
- Wang et al (2018)
  - The storm that was
    - WRF downscaling of the GFS initial condition data
  - The storm that might have been.
    - Same but perturbed by the CESM LE (about 1C attributable warming in the Gulf of Mexico)
  - **Climate change increased Harvey's precipitation by 20%**



Wang et al. (2018) "Quantitative Attribution of Climate Effects on Hurricane Harvey's Extreme Rainfall in Texas." *Environmental Research Letters* 13:054014.

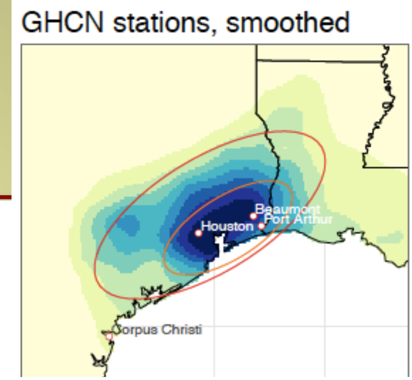
Pearl Causal inference without a storyline (“Traditional”)

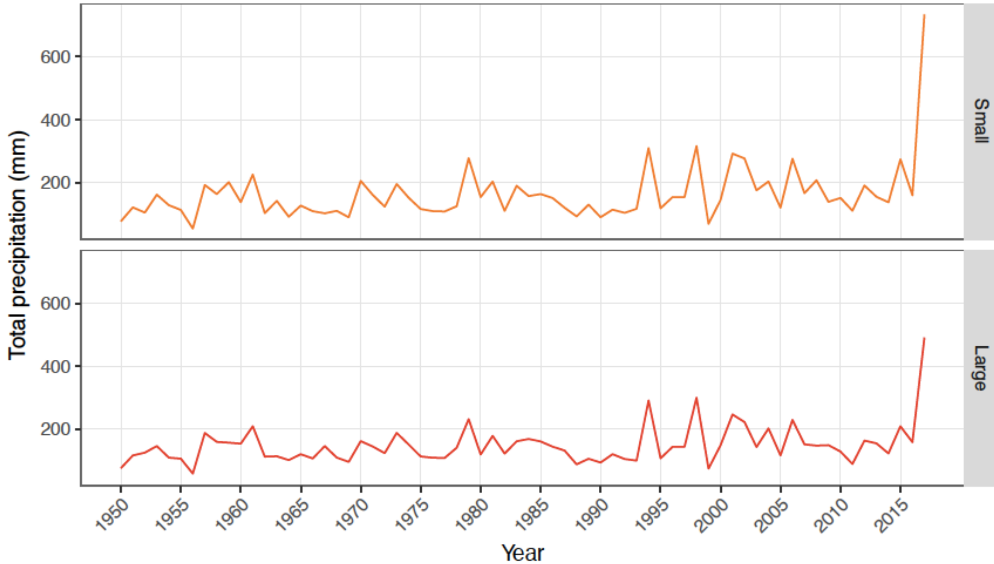
- van Oldenborg et al 2017
- 3 climate models. EC-Earth, GFDL HiFlor, HadRM3p
  - Ensembles of longer runs of varying length.
  - Harvey was not wired in by initial conditions.
- Plus a GEV statistical model to estimate rarity from CPC observations.
  - Combined this information.
  - *Likely* range of precipitation increase of 8-19%



van Oldenborg et al. (2017). “Attribution of Extreme Rainfall from Hurricane Harvey, August 2017.” *Environmental Research Letters* 12:124009.

Hurricane Harvey (Risser & Wehner 2017)





$$G_t(z) \equiv \mathbb{P}(Z_t \le z) = \exp\left\{-\left[1+\xi_t\left(\frac{z-\mu_t}{\sigma_t}\right)\right]^{-1/\xi_t}\right\}$$

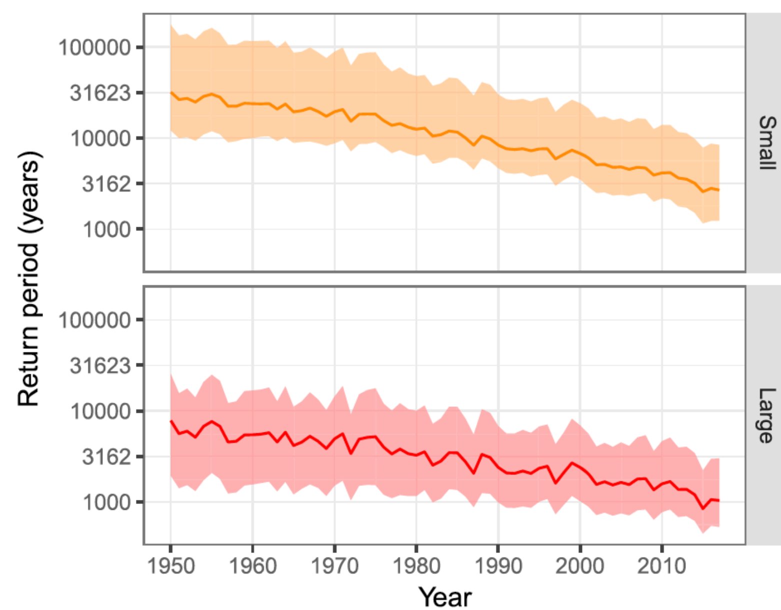
$$\mu_t = \beta_0 + \beta_1 x_{1t} + \beta_2 x_{2t}, \log \sigma_t = \phi_0 + \phi_1 x_{1t}, \xi_t \equiv \xi$$

$1=\ln(CO_2)_t$
$2=NINO3.2_t$
Best fit, AIC

Harvey seven day total precipitation

Data source	Small region Pr (mm)	Large region Pr (mm)
GHCN stations (raw values)	735.0	491.6
GHCN stations (smoothed)	700.2	481.6
NOAA AHPS	829.3	552.4

Harvey precipitation return periods in 2017
(best estimates of the actual storm)
Small region: 3000 years
Large region: 1100 years



Hurricane Harvey (Risser & Wehner 2017)

Consider this Granger attribution statement on the change in magnitude of total Hurricane Harvey precipitation, altering the co-variates in the statistical model: A “statistical counterfactual”

By fixing the probability at actual 2017 levels (1/3000 or 1/1100), we can estimate precipitation storm total amounts at that rarity with 2017 values of Niño3.4 but 1950 values of CO_2 and compare to actual 2017 storm totals.

Small region: 38% increase (likely at least 19%
Large region: 24% increase (*likely* at least 7%)

Mark D. Risser and Michael F. Wehner (2017) Attributable human-induced changes in the likelihood and magnitude of the observed extreme precipitation in the Houston, Texas region during Hurricane Harvey. *Geophysical Review Letters*. 44, 12,457–12,464. https://doi.org/10.1002/2017GL075888

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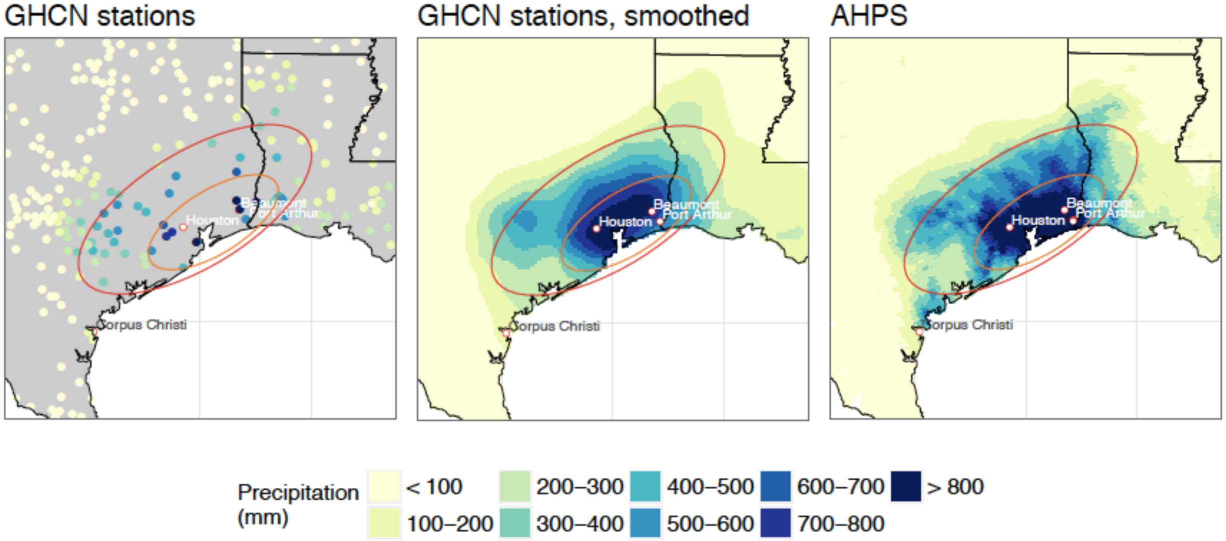


Rain to flood

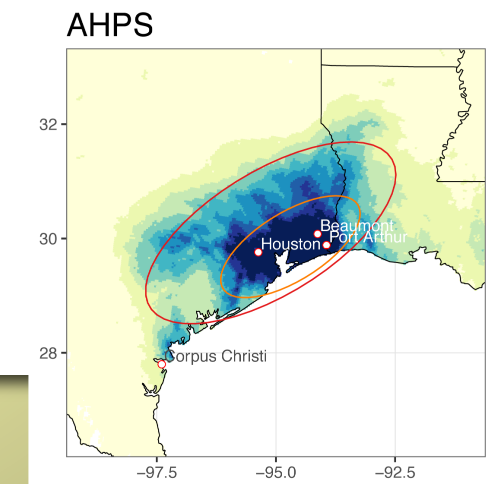
- How did this attributable increase in precipitation affect the flood?
- Design a storyline attribution analysis of the flood. (Pearl causality)

The “flood that was”.

- Fathom 30m hydraulic model driven by precipitation from the NOAA National Weather Service Advanced Hydrologic Prediction Service (AHPS)

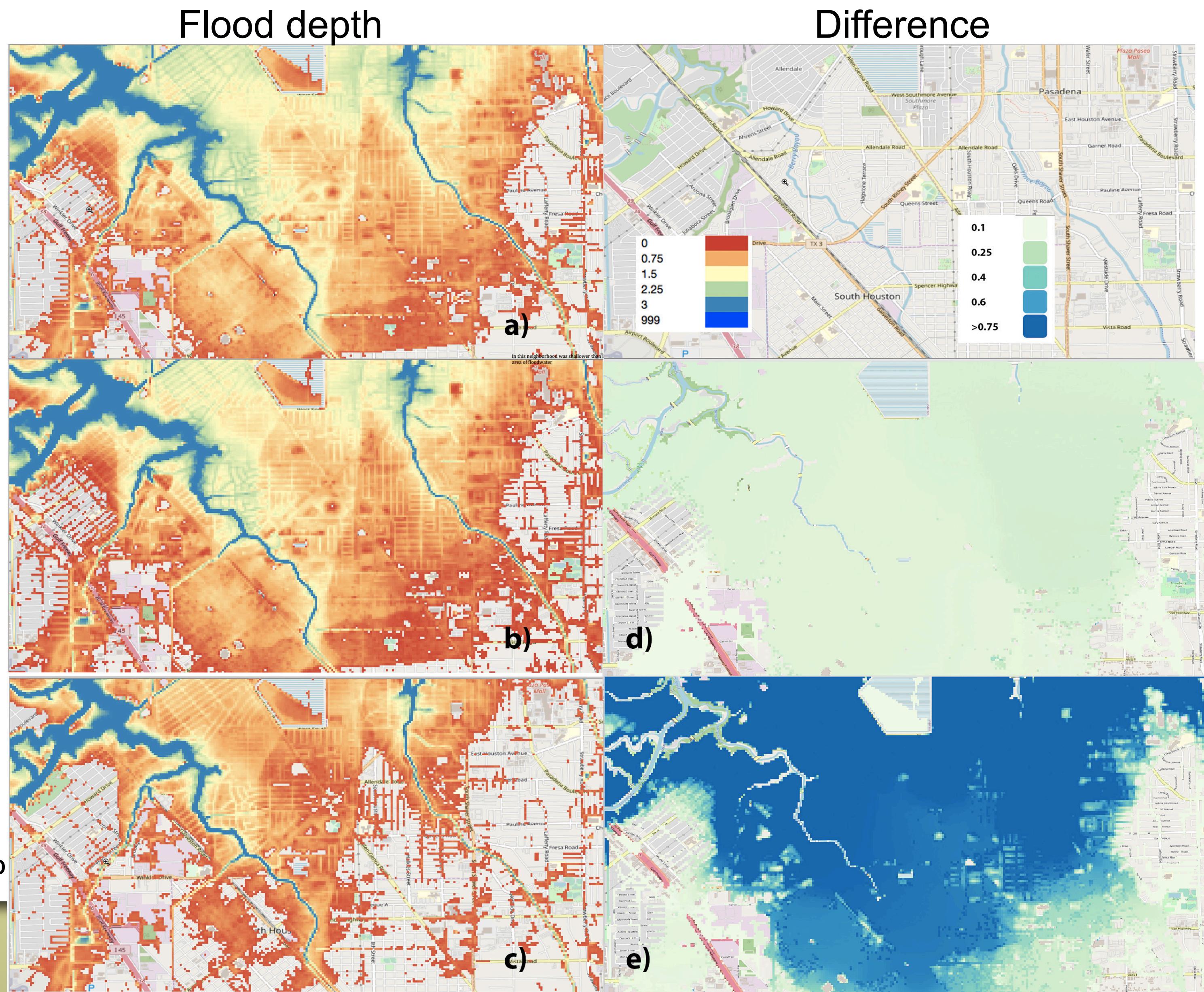
The “flood(s) that might have been”.

- Alter the rainfall uniformly by the published attribution statements.
- Published ranges are 7-38% increases
- e.g. Risser & Wehner’s 24% statement
  - Decrease observed precipitation by 1/1.24=0.81



Michael Wehner and Christopher Sampson (2021) Attributable human-induced changes in the magnitude of flooding in the Houston, Texas region during Hurricane Harvey. *Climatic Change.* 166, 20 https://doi.org/10.1007/s10584-021-03114-z

Did climate change flood my South Houston house?



actual flood that was

Flood that might have been if precipitation was increased by 7%

Flood that might have been if precipitation was increased by 38%

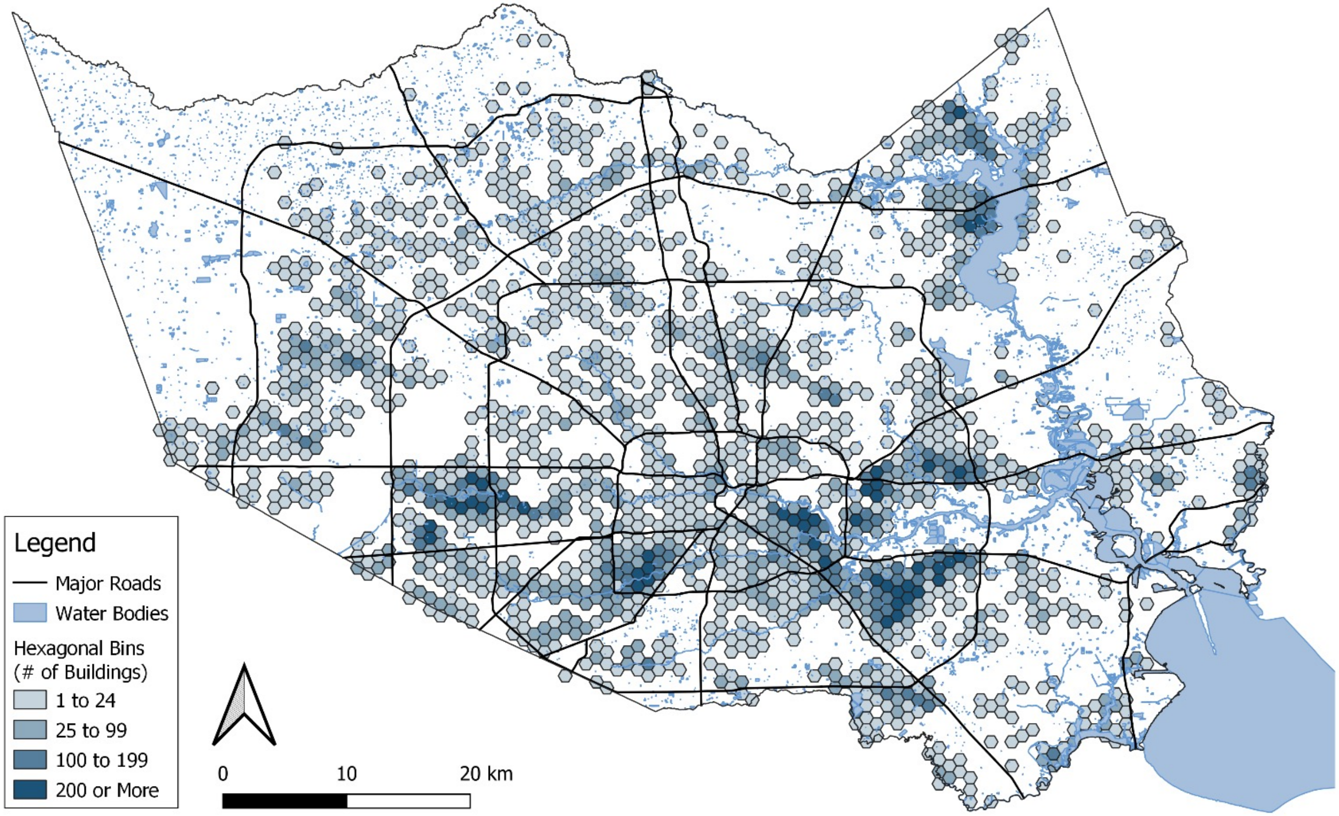
What is a crude estimate of the climate change cost of Harvey?

rain increase	flood area increase	Mechanistic attributable cost	RR
19%	14%	US$13Bn	4

- A best estimate of the insured losses from Hurricane Harvey is US$90Bn.
- Two attribution statements:
- "Our best estimate is that climate change increased the cost of Hurricane Harvey by about 14% or US$13Bn".
- "The probability of a US$90Bn hurricane loss in Texas was quadrupled due to climate change."

Flood to impacts

Combine the flood maps of Wehner & Sampson with real estate maps



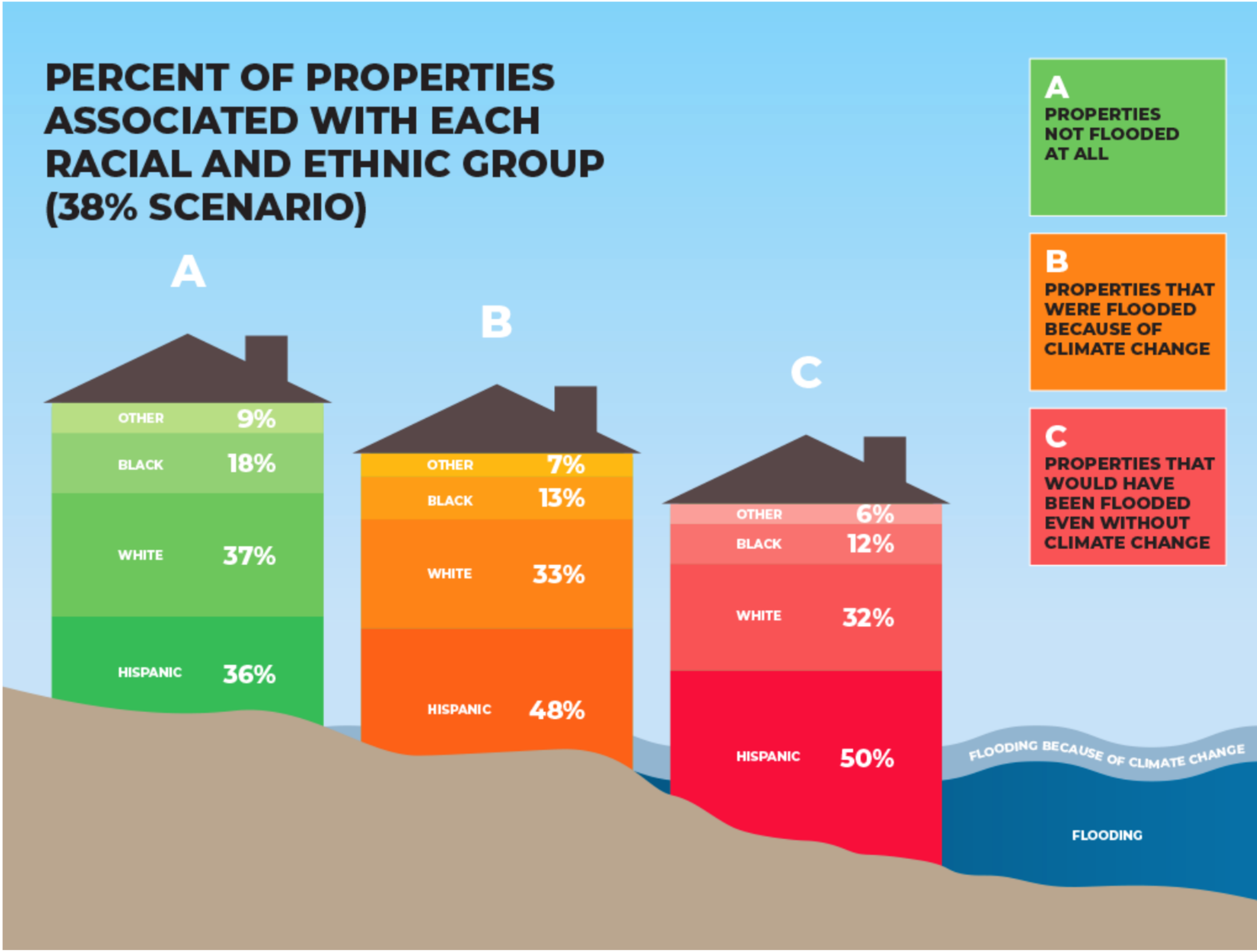
Each hexagonal bin symbolizes the number of residential buildings that would not have flooded without the added impact of climate change in Harris County, Texas during Hurricane Harvey (38% precipitation increase).

Kevin T. Smiley, Ilan Noy, Michael Wehner, Dave Frame, Christopher Sampson and Oliver E.Wing (2022) Social Inequalities in Climate Change-Attributed Impacts of Hurricane Harvey. *Nature Communications* **13**, 3418 https://doi.org/10.1038/s41467-022-31056-2

Flood to impacts

- 32% of flooded homes in Harris County would not have been flooded without climate change (best estimate, 20% precipitation increase).
  - 75% of the flooded homes were outside the Federal 100 year flood plain and thus uninsured.
    - NOAA estimated loss=$120Bn
    - Deutsche Re/Swiss Re insured loss=$90Bn

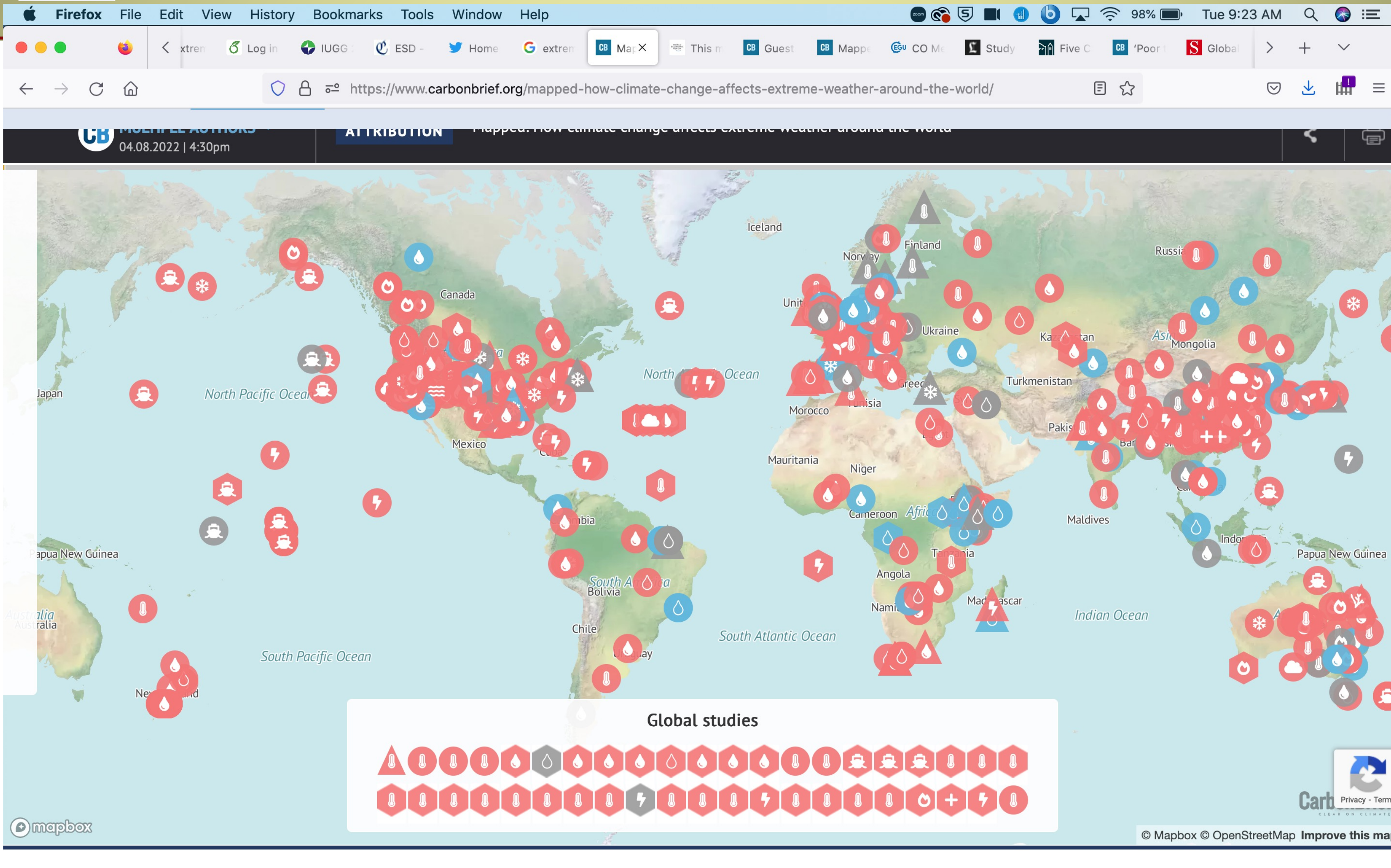
- Using census data permits further socioeconomic analysis
  - Income & Race
  - Single/multi-family residence
  - Mobile homes


PERCENT OF PROPERTIES ASSOCIATED WITH EACH RACIAL AND ETHNIC GROUP (38% SCENARIO)
A
OTHER 9%
BLACK 18%
WHITE 37%
HISPANIC 36%
B
OTHER 7%
BLACK 13%
WHITE 33%
HISPANIC 48%
C
OTHER 6%
BLACK 12%
WHITE 32%
HISPANIC 50%
A PROPERTIES NOT FLOODED AT ALL
B PROPERTIES THAT WERE FLOODED BECAUSE OF CLIMATE CHANGE
C PROPERTIES THAT WOULD HAVE BEEN FLOODED EVEN WITHOUT CLIMATE CHANGE
FLOODING BECAUSE OF CLIMATE CHANGE
FLOODING

Socio-economic disparity

- Harvey flood damages were not distributed equally across socio-economic groups.
  - Regardless of precipitation change estimate, low-income Hispanic communities were disproportionately affected.
  - In high income (white) neighborhoods, the richer you were the greater the financial damage.
  - In low income, Hispanic neighborhoods, the poorer you were, the greater the financial damage.
  - No statistical significance of income trends in non-white, non-Hispanic neighborhoods.

Weather event attribution studies



https://www.carbonbrief.org/mapped-how-climate-change-affects-extreme-weather-around-the-world/

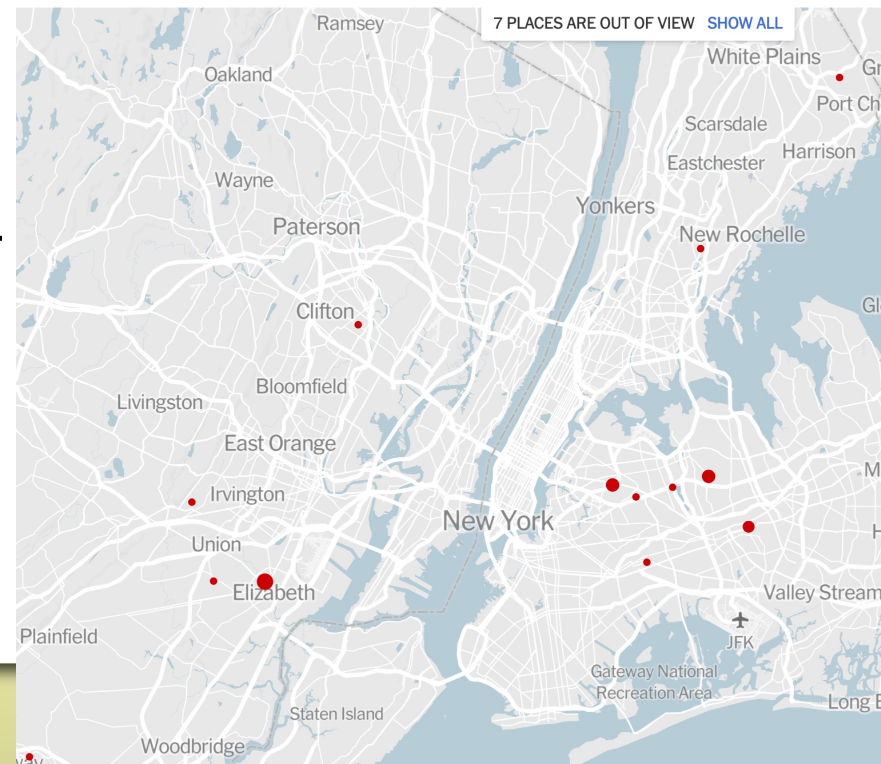
Extending to Hurricane Ida remnants

- Joint work as part of the ICOM project with Michelle Li & Dave Judi (PNNL)
- Hurricane Ida remnants were deadly in New York & New Jersey
- New York

How the Storm Turned Basement Apartments Into Death Traps

At least 11 people were found dead in basements after torrential rains flooded New York City — nearly as many as those killed by Hurricane Ida in Louisiana, where the storm made landfall.

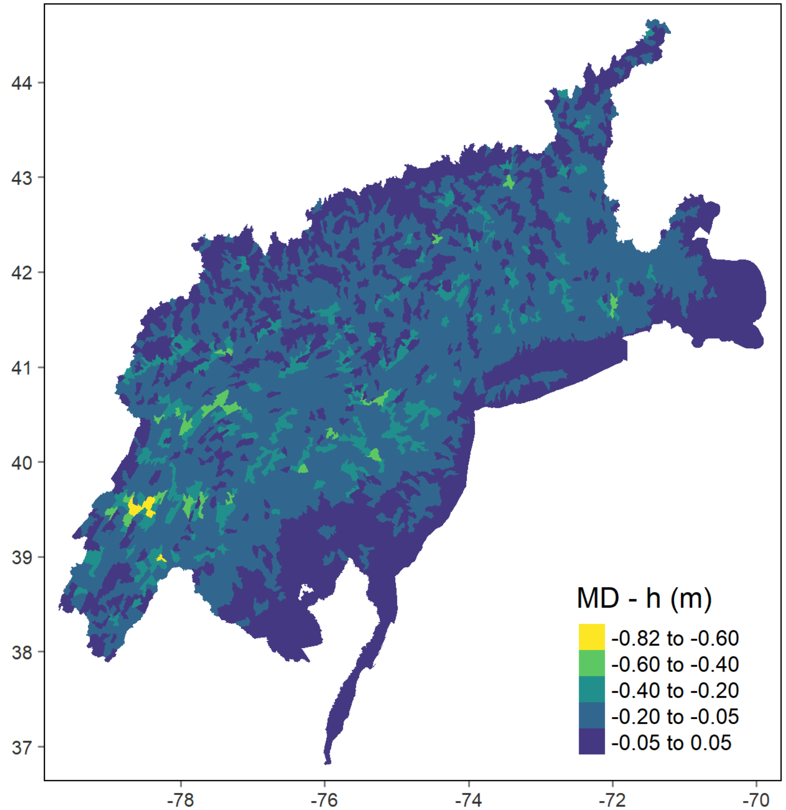
- Complex topography of the mid-Atlantic.
  - Hydrologic model (not hydraulic)
  - RIFT
  - Rapid Infrastructure Flood Tool

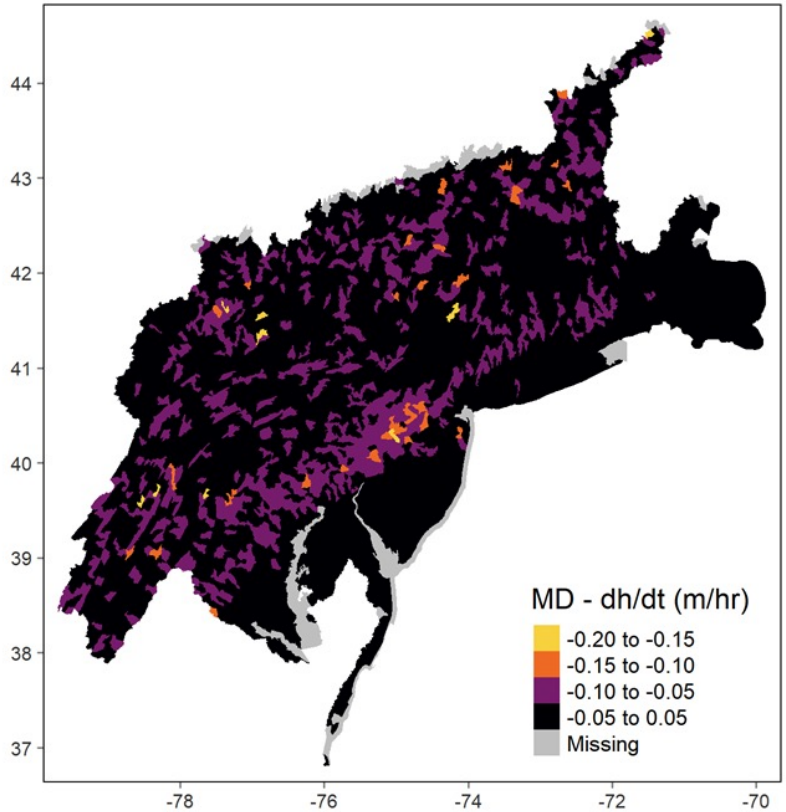


Extending to Hurricane Ida remnants

More complex topography requires a more complex hydrologic model (RIFT).

Analysis is ongoing. Also revealing socioeconomic disparity





Xue (Michelle) Li, Michael Wehner, David Judi. Quantifying Human Effect on the Flood from the Remnants of Ida with RIFT Simulations (in preparation)

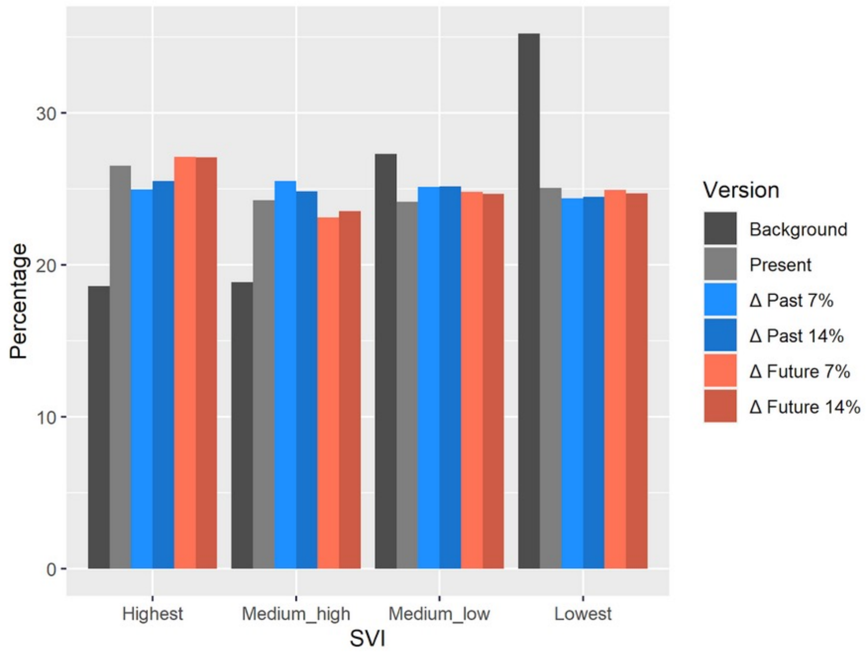
Attributable Ida flood impacts

- Flooding is not uniform
- Neither is the population

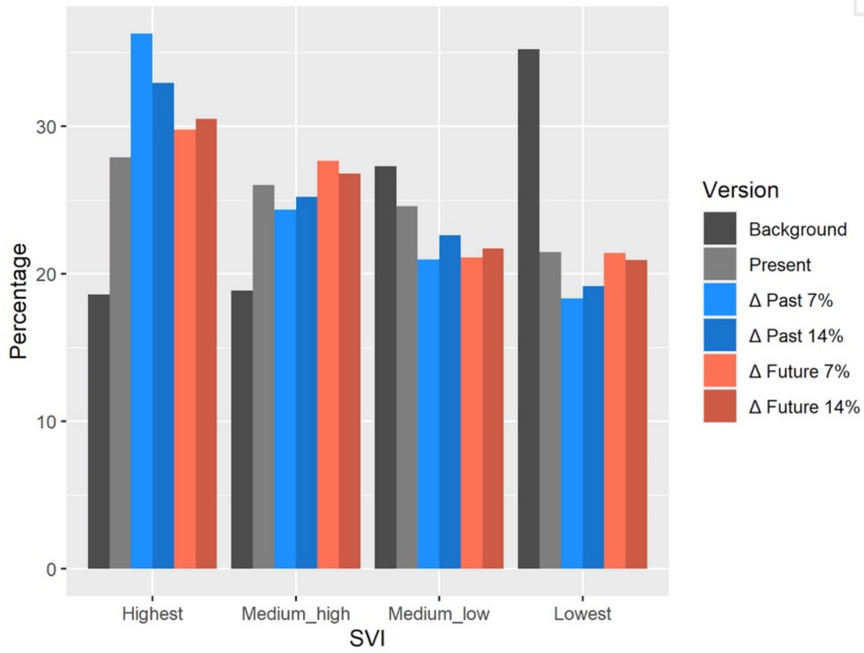
	Present	P14%	P7%	F7%	F14%
Inundation area of developed lands (thousand km2)	4.1	-0.32 (-7.8%)	-0.17 (-4.1%)	+0.17 (+4.3%)	+0.34 (+8.3%)
Total population exposed to floodwater (million)	5.46	-0.45 (-8.3%)	-0.24 (-4.3%)	+0.25 (+4.6%)	+0.50 (+9.1%)

Attributable Ida social inequality

- Environmental injustice exists even without climate change
  - Compare gray to black
- Here, SVI = CDC/ATSDR Social Vulnerability Index
- Climate change did not alter EJ at low flood depths (compare color to gray)
  - But exacerbated at deeper depths



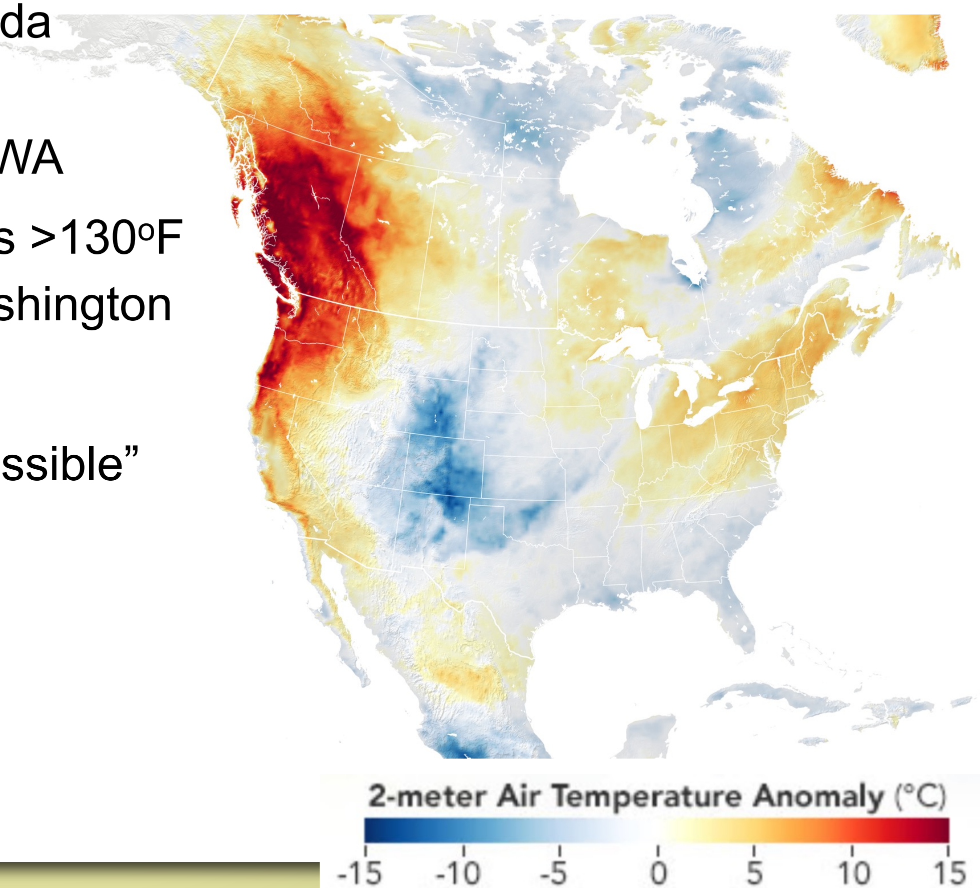
SVI 0.15m (0.5 ft) threshold



SVI 1m (3 ft) threshold

The Pacific Northwest heatwave of 2021

- Unprecedented temperatures reached across the region
  - June 25– July 7
  - Records were shattered
- Air temperatures reached 120^{o}F in Canada
  - Resulting fires destroyed Lytton, BC.
  - Temperatures exceeded 115^{o}F in OR/WA
- Satellite estimate of ground temperatures >130^{o}F
  - Maximum of 145^{o}F in Wenatchee, Washington
- Over 1400 deaths (Wikipedia)
- WWA: Such temperatures “virtually impossible” without climate change.
  - www.worldweatherattribution.org

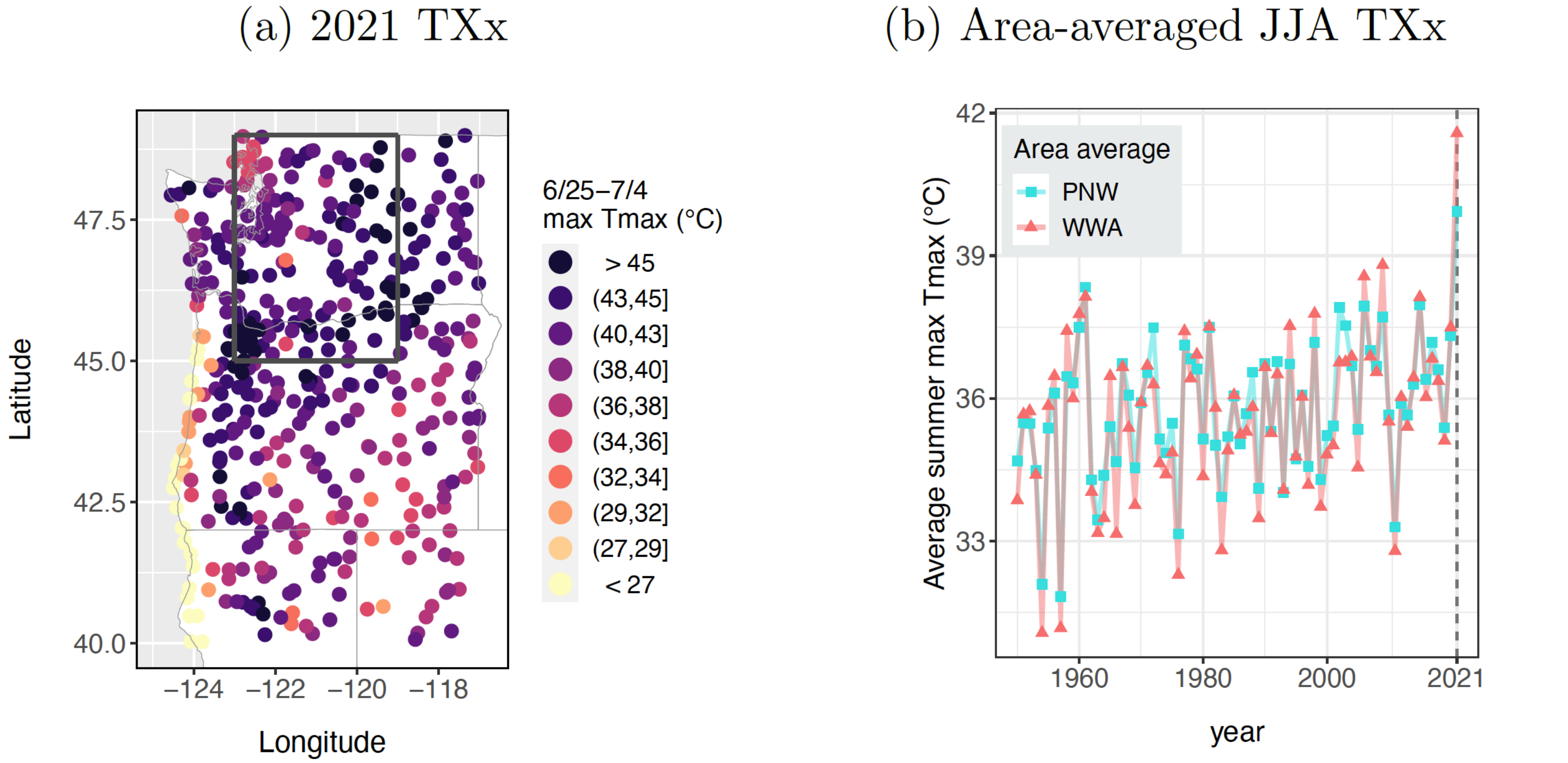


June 27, 2021 Figure credit: NASA

https://www.worldweatherattribution.org/wp-content/uploads/NW-US-extreme-heat-2021-scientific-report-WWA.pdf

Record shattering temperatures

- A 4.5σ event
- But not Gaussian, of course.
- Extreme value distributions are the appropriate statistical tool.



Generalized Extreme value distributions

- GEV is a 3 parameter distribution, assuming stationarity

$$p_t(\boldsymbol{s}, u(\boldsymbol{s})) = \begin{cases} 1 - \exp\left\{-\left[1 - \xi_t(\boldsymbol{s})\left[\left(\mu_t(\boldsymbol{s}) - u(\boldsymbol{s})\right)\right]/\sigma_t(\boldsymbol{s})\right]^{-1/\xi_t(\boldsymbol{s})}\right\}, & \xi_t(\boldsymbol{s}) \neq 0, \\ 1 - \exp\left\{-\exp\left\{\left[\left(\mu_t(\boldsymbol{s}) - u(\boldsymbol{s})\right)\right]/\sigma_t(\boldsymbol{s})\right\}\right\}, & \xi_t(\boldsymbol{s}) = 0. \end{cases}$$

Location $\mu_t(\boldsymbol{s}) = \mu_0(\boldsymbol{s}) + \mu_1(\boldsymbol{s})\mathrm{GHG}_t + \mu_2(\boldsymbol{s})\mathrm{PDSI}_t(\boldsymbol{s}) + \mu_3(\boldsymbol{s})\mathrm{ELI}_t + \mu_4(\boldsymbol{s})\mathrm{Urban}_t(\boldsymbol{s}),$

Scale $\log\sigma_t(\boldsymbol{s}) = \sigma_0(\boldsymbol{s}) + \sigma_1(\boldsymbol{s})\mathrm{GHG}_t + \sigma_2(\boldsymbol{s})\mathrm{ELI}_t,$

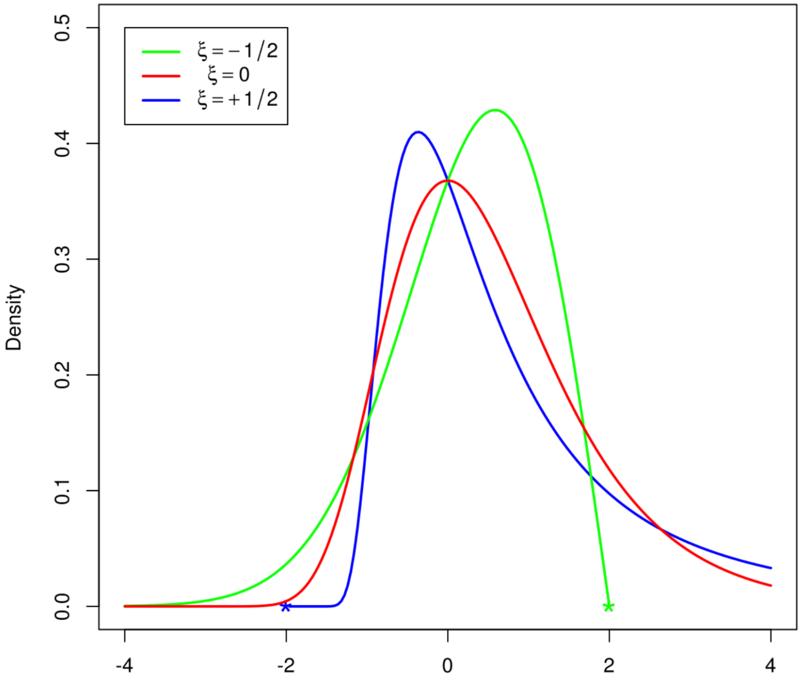
Shape $\xi_t(\boldsymbol{s}) \equiv \xi(\boldsymbol{s}),$

- Various tools to fit these parameters
- We break stationarity by introducing

physical covariates!!!!

- Now 9 parameters.
- Once fit, we can calculate the upper bound

$$b_t(\boldsymbol{s}) = \mu_t(\boldsymbol{s}) - \sigma_t(\boldsymbol{s})/\xi_t(\boldsymbol{s}).$$



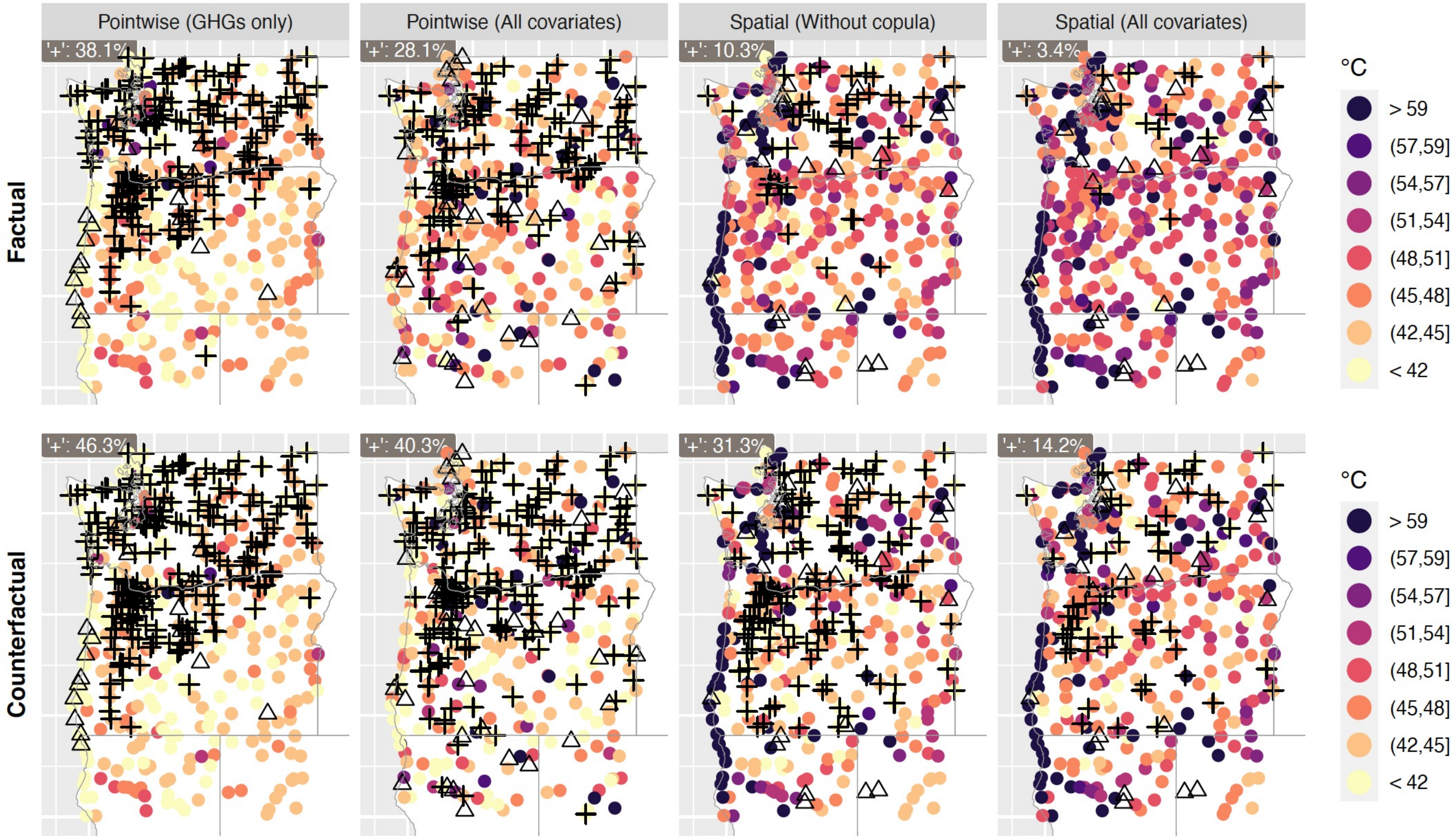
Why all this math?

- The math is important because the observed temperatures were so high
- "Simple" out of sample analysis using 1950-2020 temperatures reveals
  - Only use greenhouse gas covariate
  - Many observations exceed the statistical upper bound.
  - Even exceeding the upper bound of the upper bound.
    - (i.e. 95% confidence interval)
  - **Statistically impossible!!!!!!**
- OK, how about an in-sample fit using 1950-2021 data?
  - Goodness of fit is so bad that results are not believable.

- Actually, adding 5 more covariates didn't help as much as I thought it would.
- We then added spatial statistics.
  - Accounts for the dependence between nearby stations.
  - Essentially increases the sample size.
  - Also we added 3 more spatial covariates!

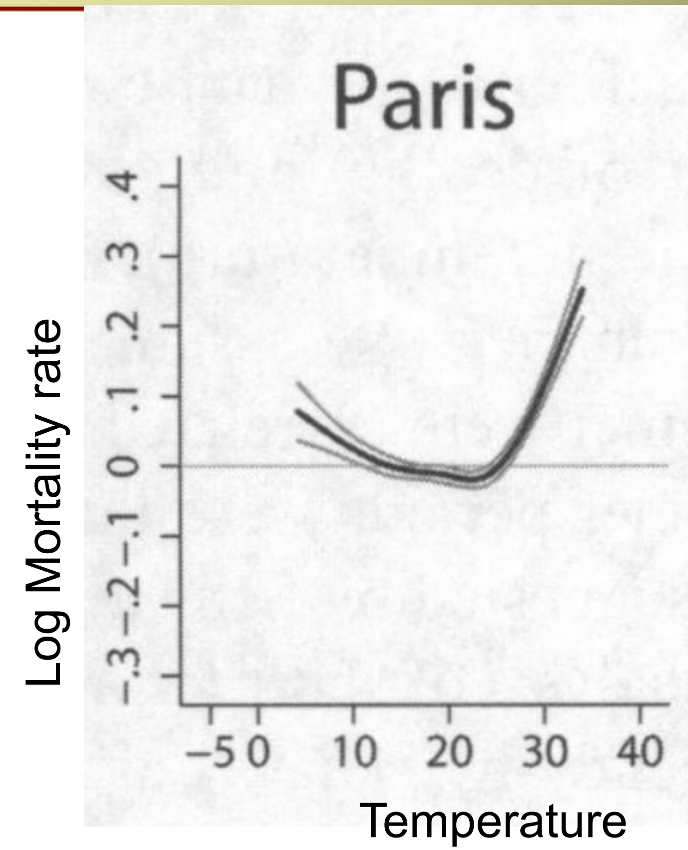
Results

Crosses are where the observed 2021 temperature exceeds the upper bound



Mortality and heat: How many people died?

- The effect of extreme heat increases dramatically with temperature.
- A mechanistic interpretation.

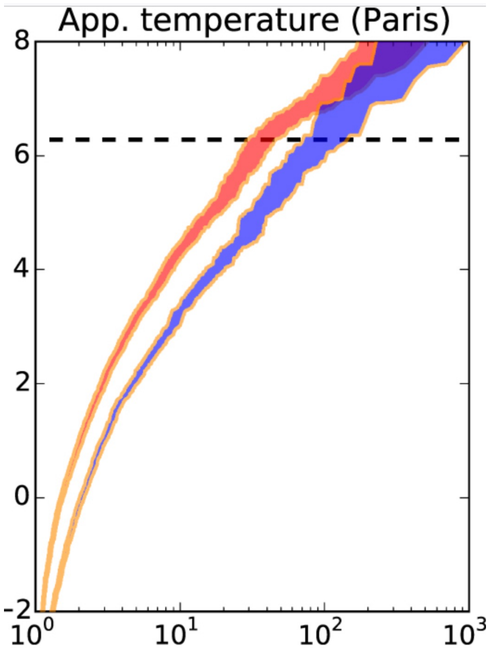


Baccini et al

1. Attribute the temperature change.
2. Subtract from the observed temperature.
3. Compare mortality rate that was to the mortality rate than ”might have been”

A more traditional approach (Mitchell et al.)

- Use the mortality rate curve to transform temperature to death.
- Pearl causality, but not a storyline.



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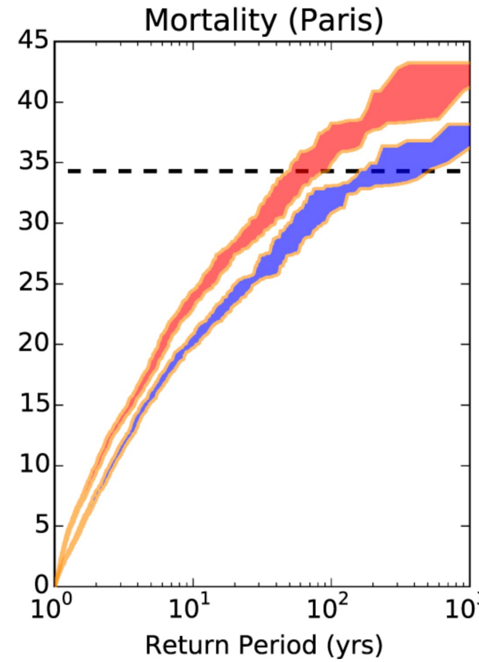


- The chances of the actual level of mortality due to heat was tripled because of climate change.
- 510 people died in Paris during the 2003 heat wave because of climate change.
- As the 2003 heat wave affected 100s of millions of people across Europe, the total increase in mortality was orders of magnitude more.

Mitchell *et al* (2016) Attributing human mortality during extreme heat waves to anthropogenic climate change *Environ. Res. Lett.* **11** 074006

End to end attribution:

Harvey:

- Global warming → more rain → more flooding → more impacts
- 1°C → 20% → 14% → 32%

- Low income Hispanic population was disproportionately affected
  - 50% of the flooded homes but only 36% of the population (even without climate change)
- The Harvey flood data is publicly available at

https://portal.nersc.gov/cascade/Harvey/

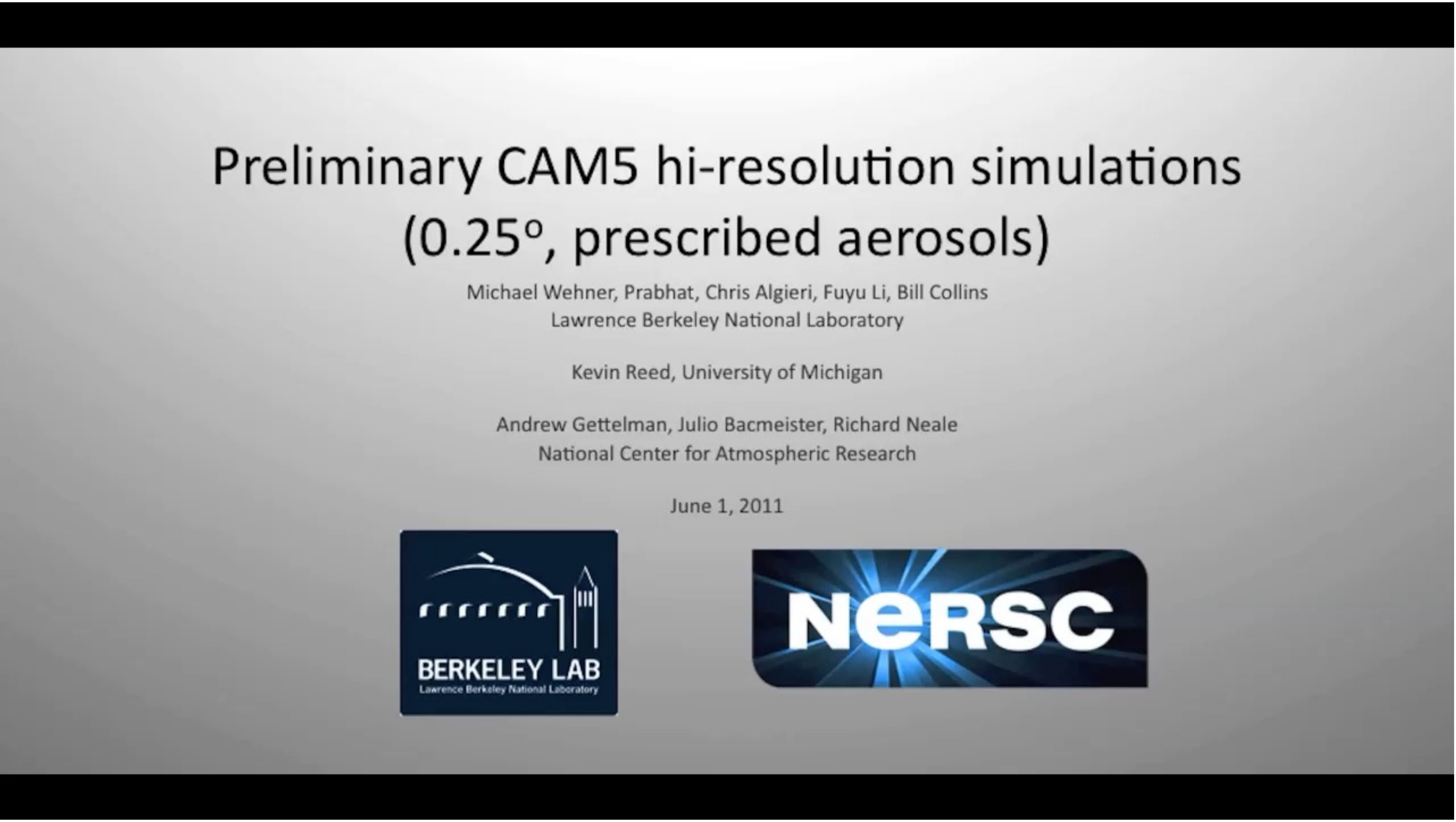
Ida:

- 500,000 people were flooded by climate change.
- Most vulnerable population more affected by deep floods due to warming
  - Least vulnerable was less affected

What does this have to do with high performance computing?

- Not much for Granger causal inference.
  - Statistical models are cheap enough for individual stations
  - Spatial statistical models are very computationally expensive
    - Other techniques. Machine Learning.
- Lots for Pearl causal inference.
  - Larger ensembles of long global model simulations
  - Multi-decadal tropical cyclone permitting (~20km) model simulations.
  - Convection permitting simulations (<4km)
    - Longer runs
    - More storylines
    - Both mean more model output data.
  - Impact models (i.e. floods) are not inexpensive at 30-60m scales.
    - More big data

Tropical Cyclone permitting simulation



3 km resolution regional climate model simulation of Hurricane Katrina (2005)

Christina Patricola, Lawrence Berkeley National Laboratory
cmpatricola@lbl.gov

Some relevant publications

- Mark D. Risser and Michael F. Wehner (2017) Attributable human-induced changes in the likelihood and magnitude of the observed extreme precipitation in the Houston, Texas region during Hurricane Harvey. *Geophysical Review Letters*. 44, 12,457–12,464. https://doi.org/10.1002/2017GL075888
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- Kevin T. Smiley, Ilan Noy, Michael Wehner, Dave Frame, Christopher Sampson and Oliver E.Wing (2022) Social Inequalities in Climate Change-Attributed Impacts of Hurricane Harvey. To appear in *Nature Communications*.
- Baccini, Michela, et al. (2008) "Heat effects on mortality in 15 European cities." *Epidemiology* 711-719.
- Mitchell *et al* (2016) Attributing human mortality during extreme heat waves to anthropogenic climate change *Environ. Res. Lett.* **11** 074006
- Perkins-Kirkpatrick, S.E., Stone, D.A., Mitchell, D.M., Rosier, S., King, A.D., Lo, Y. T. E., Pastor-Paz, J., Frame, D., Wehner, M. (2022) On the attribution of the impacts of extreme weather events to anthropogenic climate change. *Environmental Research Letters* 17 024009 https://iopscience.iop.org/article/10.1088/1748-9326/ac44c8

Thank you!

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