Institute and Faculty of Actuaries

IFoA GIRO Conference 2024

18–20 November, ICC, Birmingham

Institute and Faculty of Actuaries

Climate change and flood risk: Transforming the actuarial profession

Professor Paul Bates CBE FRS
Chairman, Fathom
Professor of Hydrology, University of Bristol

IFoA GIRO Conference 2024

Global flood risk

Average annual flood impacts 2003-2022

- 75 million people affected
- > 5,000 fatalities
- ~US$40 billion in losses

Significant upward pressure due to climate change and population growth

Delforge, D. et al.: (2023). EM-DAT: The Emergency Events Database. CRED, Belgium. https://doi.org/10.21203/rs.3.rs-3807553/v1

Climate attribution shows extremes have already changed

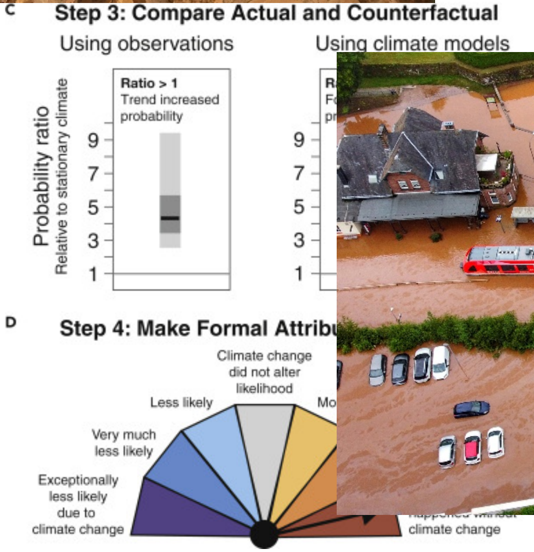
Attribution studies compare present day climate with a pre-industrial counter-factual

European floods, 2021

- Up to 1 in 500-year event
- At least 243 fatalities
- Total loss ~€10Bn
- Insured loss ~€2.5Bn

Attribution findings (today compared pre-industrial climate 1.2°C cooler)

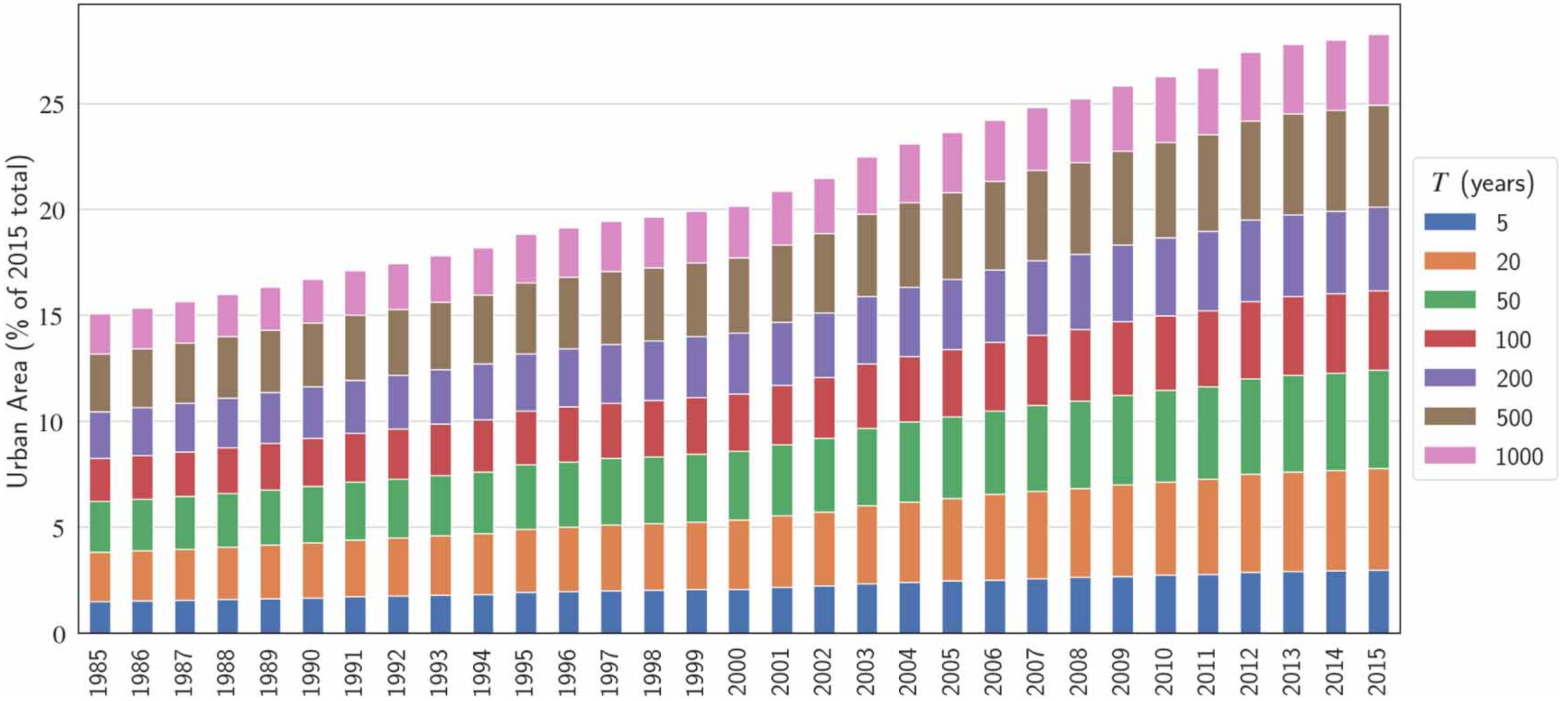
- 1-day summer rainfall 3 – 19% higher
- Event was 1.2-9x more likely



Tradowsky, J.S., Philip, S.Y., Kreienkamp, F. *et al.* Attribution of the heavy rainfall events leading to severe flooding in Western Europe during July 2021. *Climatic Change* **176**, 90 (2023). https://doi.org/10.1007/s10584-023-03502-7

D., & ... uting ... ge: A ... d. *One* ... 2020.0 5.011

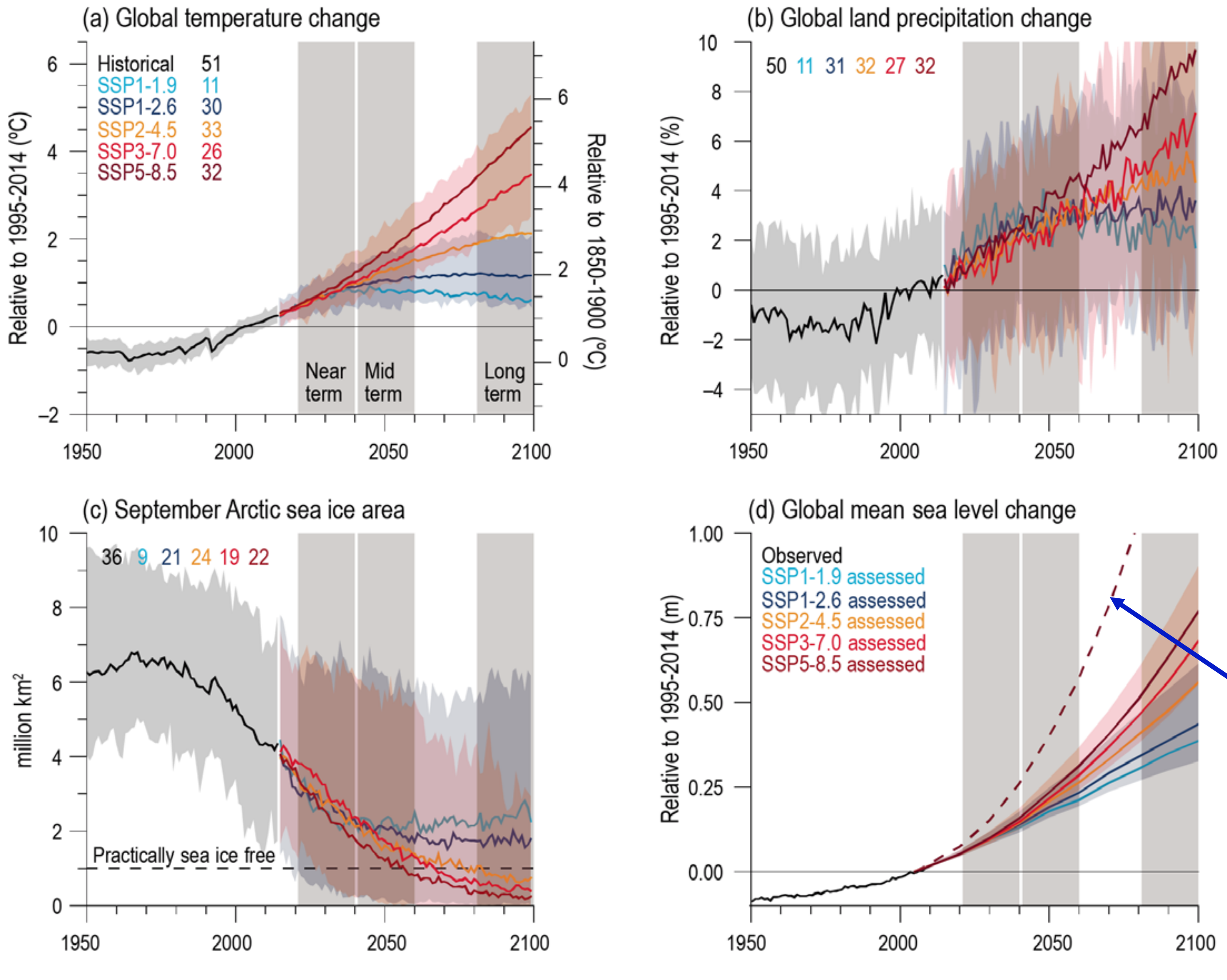
… and so has the population at risk of floods



Annual time series of global urban area (in percentage, normalized by the 2015 total urban area) on the floodplain for different flood return periods (5 to 1000 years)

Andreadis, K. M., Wing, O. E. J., Colven, E., Gleason, C. J., Bates, P. D., & Brown, C. M. (2022). Urbanizing the floodplain: global changes of imperviousness in flood-prone areas. *Environmental Research Letters*, *17*(10), 104024. https://doi.org/10.1088/1748-9326/ac9197

The future - ‘Stationarity is dead’ *



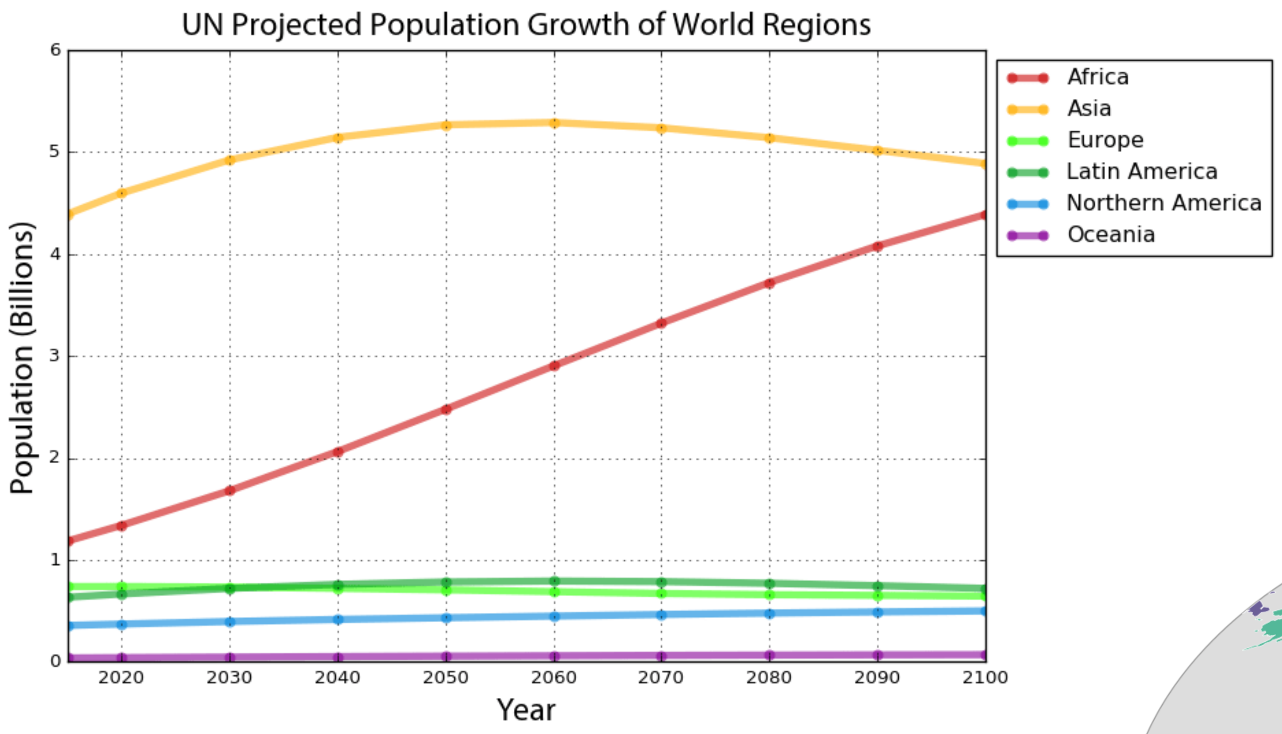
IPCC Assessment Report 6: Selected indicators of global climate change from CMIP6 historical and scenario simulations

Averages over the CMIP6 simulations, the shadings around the SSP1-2.6 and SSP3-7.0 curves show 5–95% ranges, and the numbers near the top show the number of model simulations used

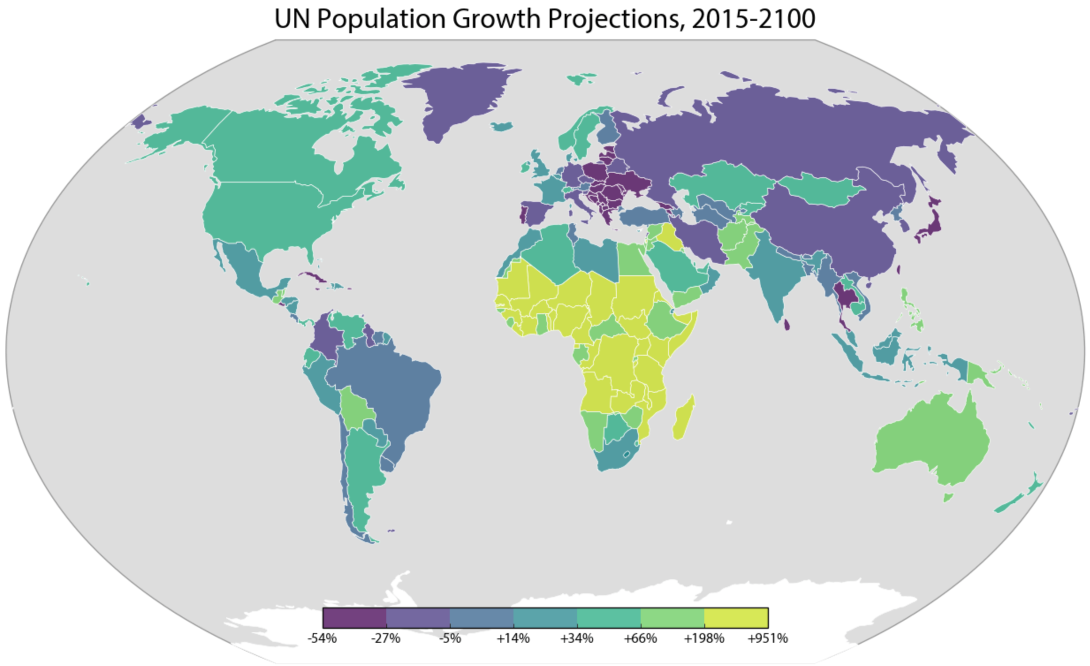
RCP8.5 Low confidence, low likelihood tail

* Milly et al. (2008). Stationarity Is Dead: Whither Water Management? *Science*, *319*(5863), 573–574. https://doi.org/10.1126/science.1151915

The future - ‘Stationarity is dead’



- Population change
- Migration
- Ageing
- Urbanization
- Concentration of risk



Boeing, G. (2015). World Population Projections. Retrieved October 14, 2024, from https://geoffboeing.com/2015/12/world-population-projections/

Flood risks are increasing

Causing uncontrolled outcomes for insurers

1/3

of the world's population is exposed to flooding.

Flood is now the world's most prevalent natural disaster.

30% ↑

increase in insured losses from flood events in 2012-2021 from preceding decade.

Flood is no longer a secondary peril.

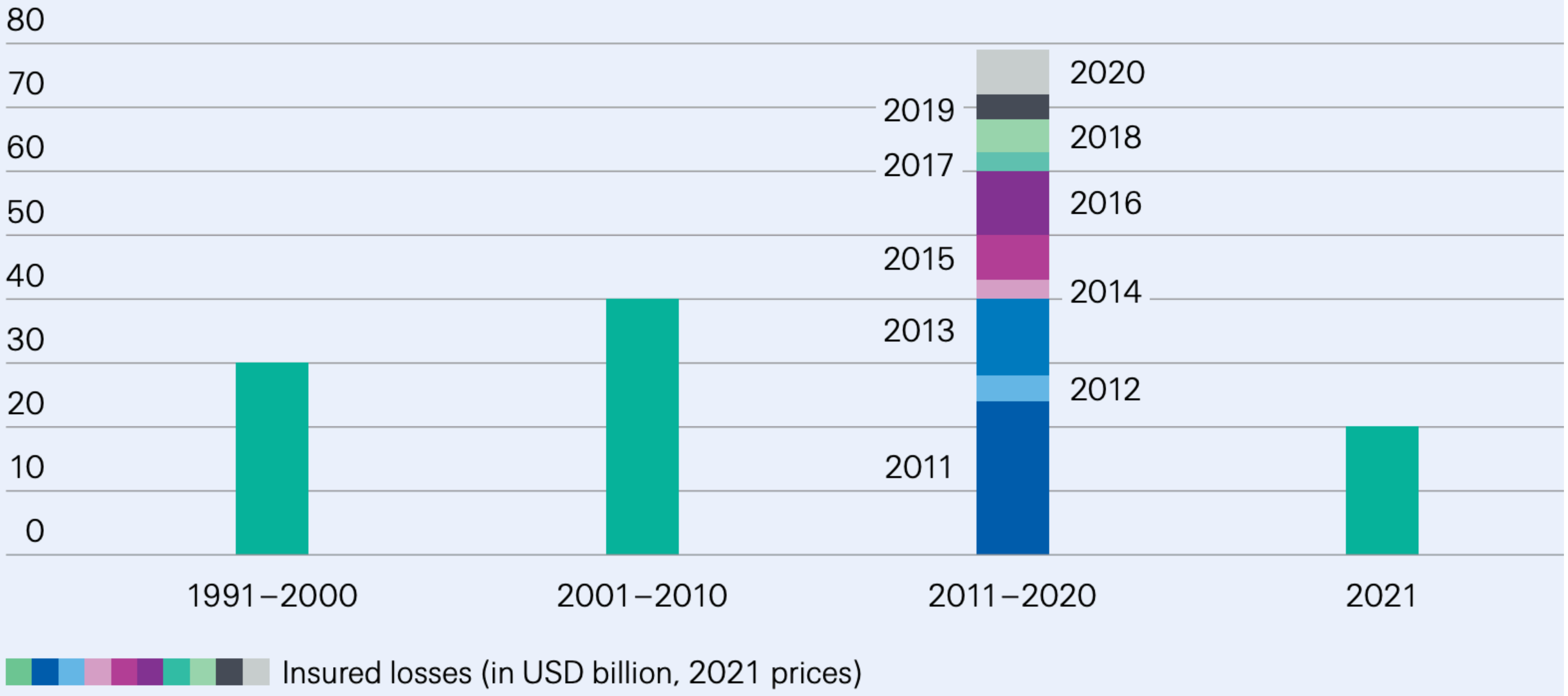
1.2tn

In the past 30 years, floods have led to over USD 1.2tn in global economic losses.

Global flood losses are increasing and expected to worsen.

*Swiss Re Institute Sigma Reports**

Insured losses have almost doubled



Source: Swiss Re Institute

Flood models have lagged significantly

Thailand, 2011–‘Unmodelled Loss’

$47bn

Economic losses

$18bn

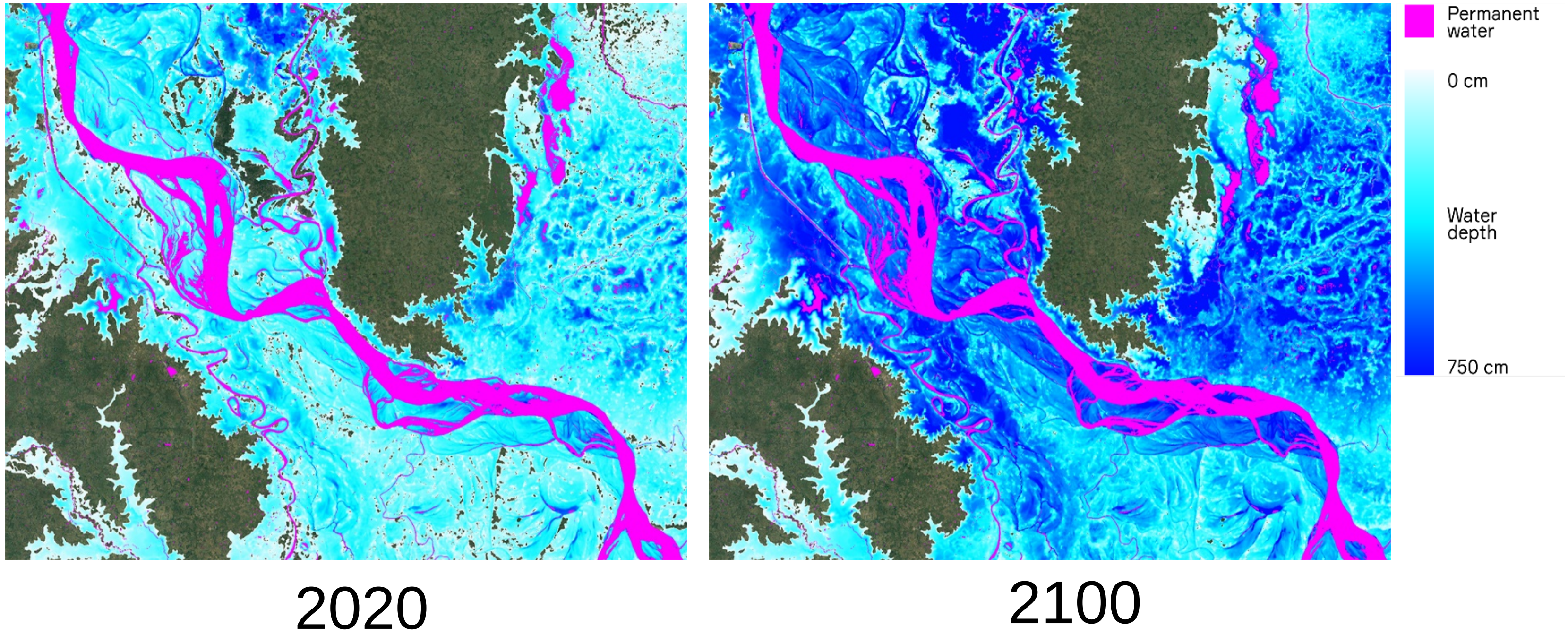
Insured losses

A market failure

But why should actuaries take notice?

- Past ≠ Future
- In fact, Past ≠ Present Day

- Even short-term views of risk, e.g. for insurers, are impacted
- … and an increasing number of clients want longer-term views
  - Performance of investment portfolios over time
  - Threats to infrastructure investments
  - Supply chain risks
  - Stress testing
  - Regulatory compliance



Ganges/Padma river, showing fluvial defended flood inundation map for 2020 and 2100.

And for this we need data

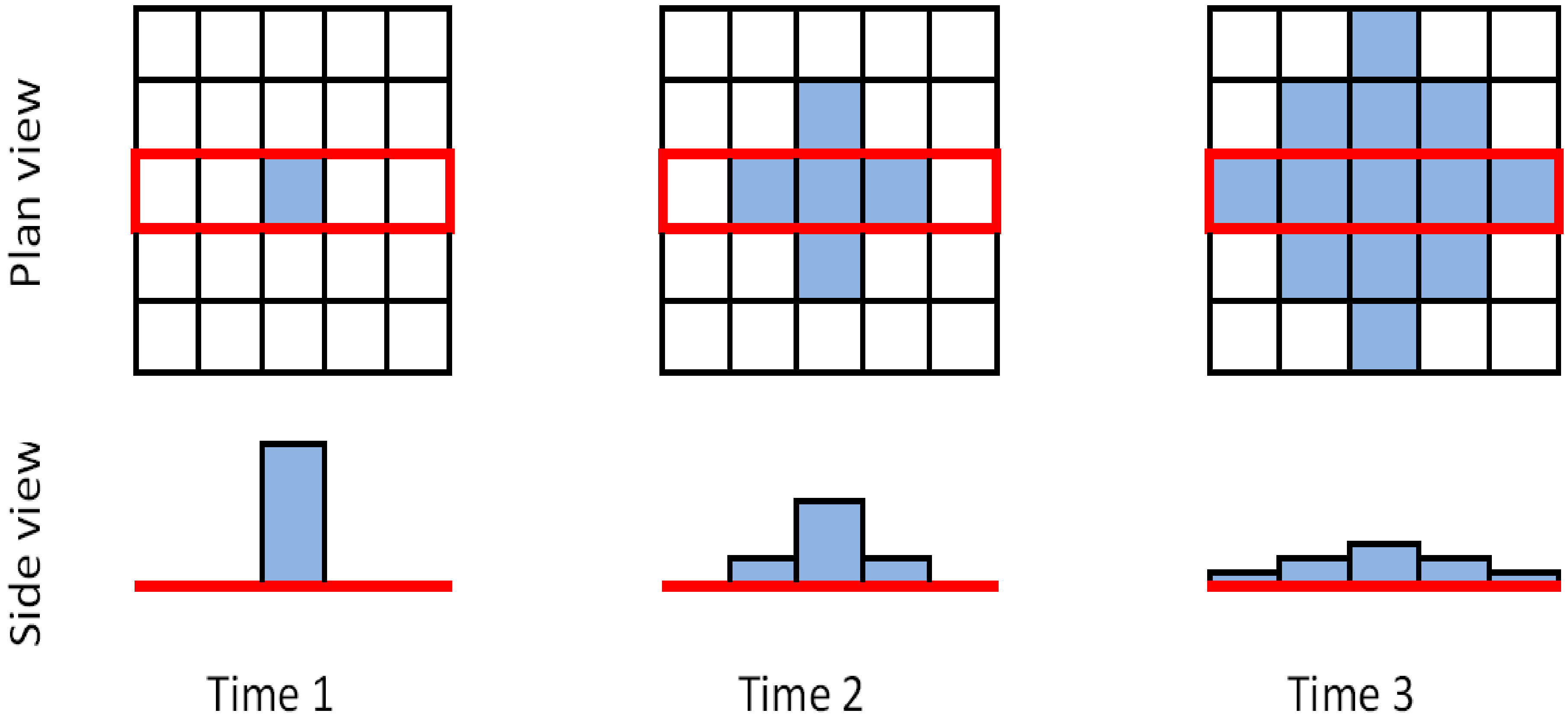
“The rise of data science in actuarial work represents a paradigm shift from a reactive to a proactive approach, transforming the role of actuaries from mere number crunchers to strategic advisors armed with cutting-edge analytical tools.”

— Cynthia Walumbe, President - Actuarial Students’ Society of Kenya.

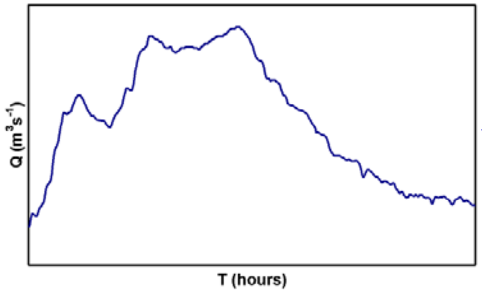
What can we do about it?

For floods, actually quite a lot

How do inundation models work?

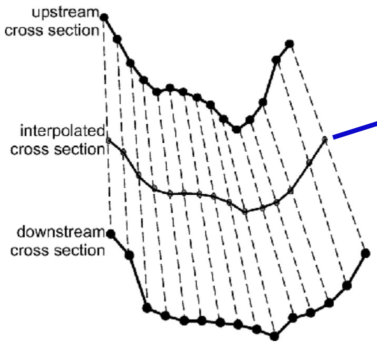


Creating models: the building blocks



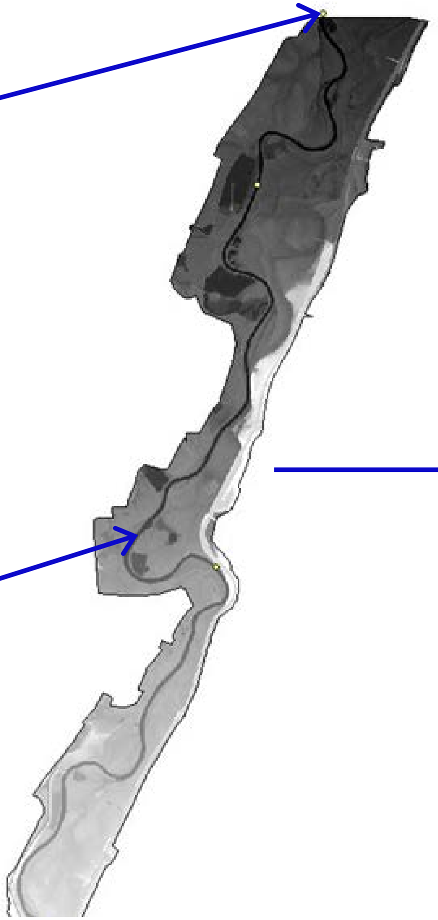
Inflow hydrograph (QT)

Eg: Gauging station records



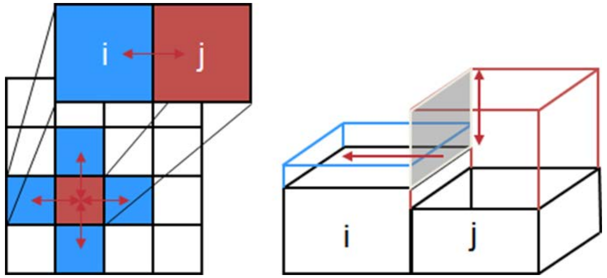
Channel bathymetry

Eg: Surveyed channels



Terrain data

Eg: LiDAR

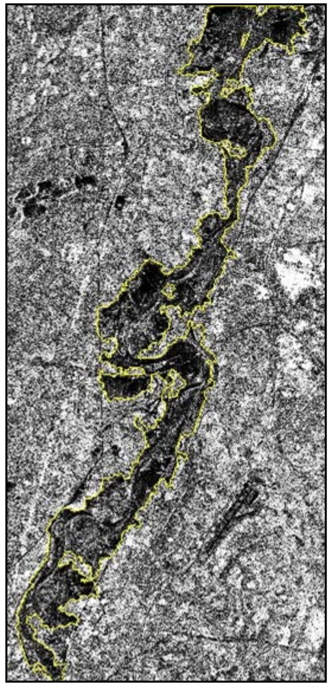


Hydraulic engine

Eg: LISFLOOD-FP

Bates, P. D., Horritt, M. S., & Fewtrell, T. J. (2010). A simple inertial formulation of the shallow water equations for efficient two-dimensional flood inundation modelling. *Journal of Hydrology*, *387*(1), 33–45. https://doi.org/10.1016/j.jhydrol.2010.03.027

Voila!



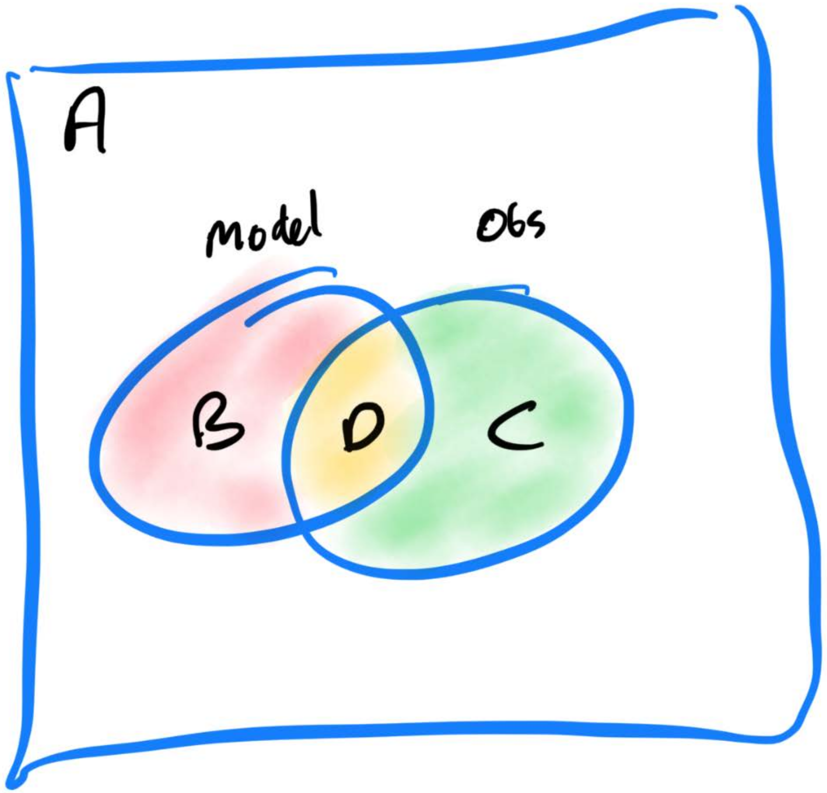
Inundation extent derived from satellite imaging radar

Source: SAR imagery processed using a statistical active contour model (Horritt, 1999)

Performance metrics

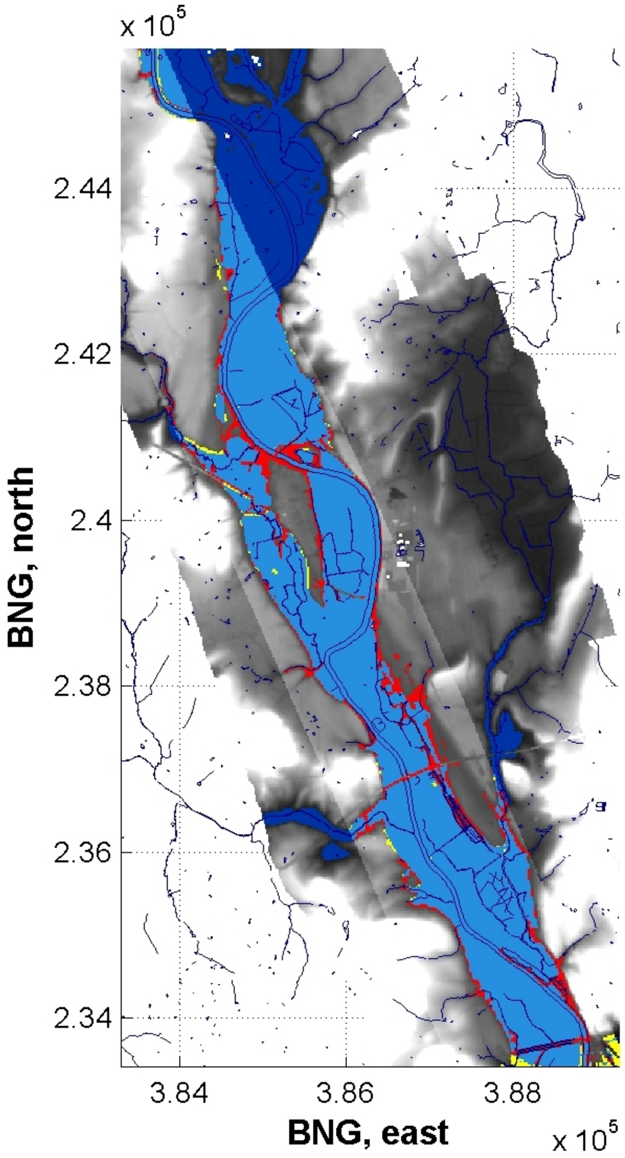
- Flood extent – Critical Success Index

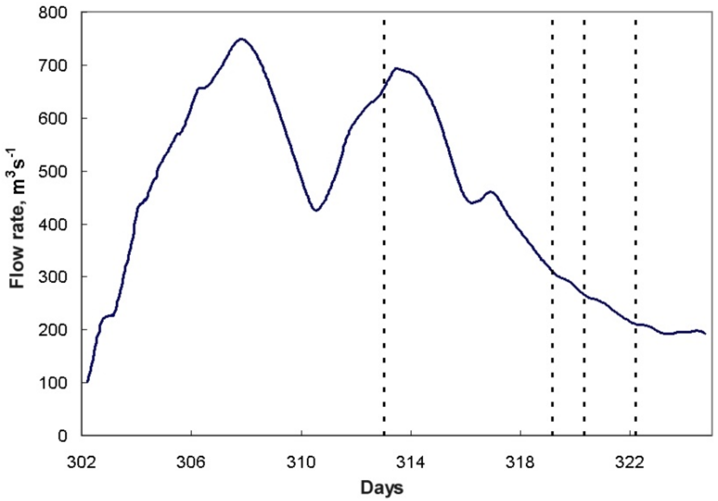
- Water depth - Root Mean Squared Error



$$CSI = \frac{D}{B+C+D}$$

Model vs Radar: 8 November 2000

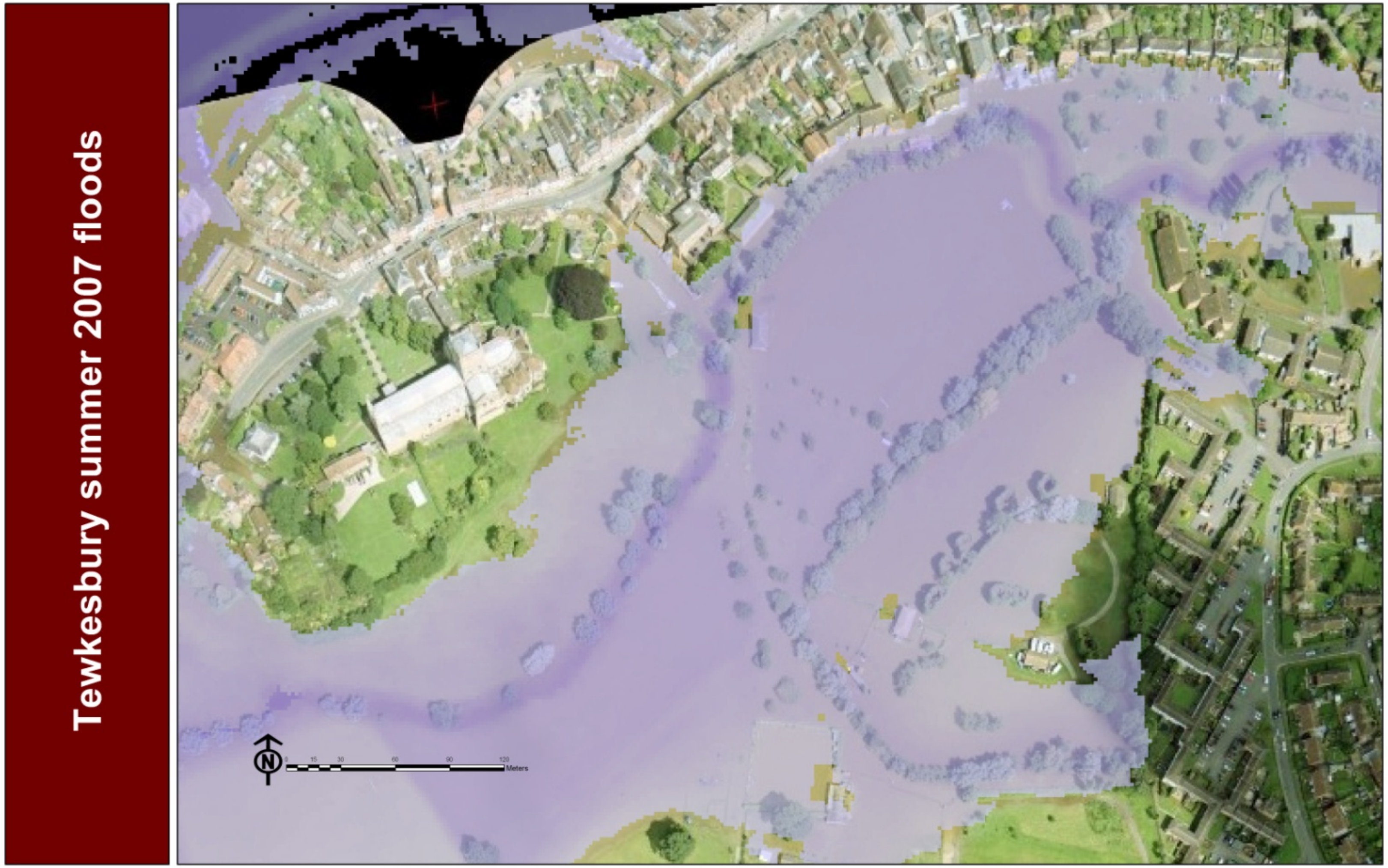




- = correct
- = over-prediction
- = under-prediction
- = predicted as flooded, no ASAR coverage

CSI = 89%

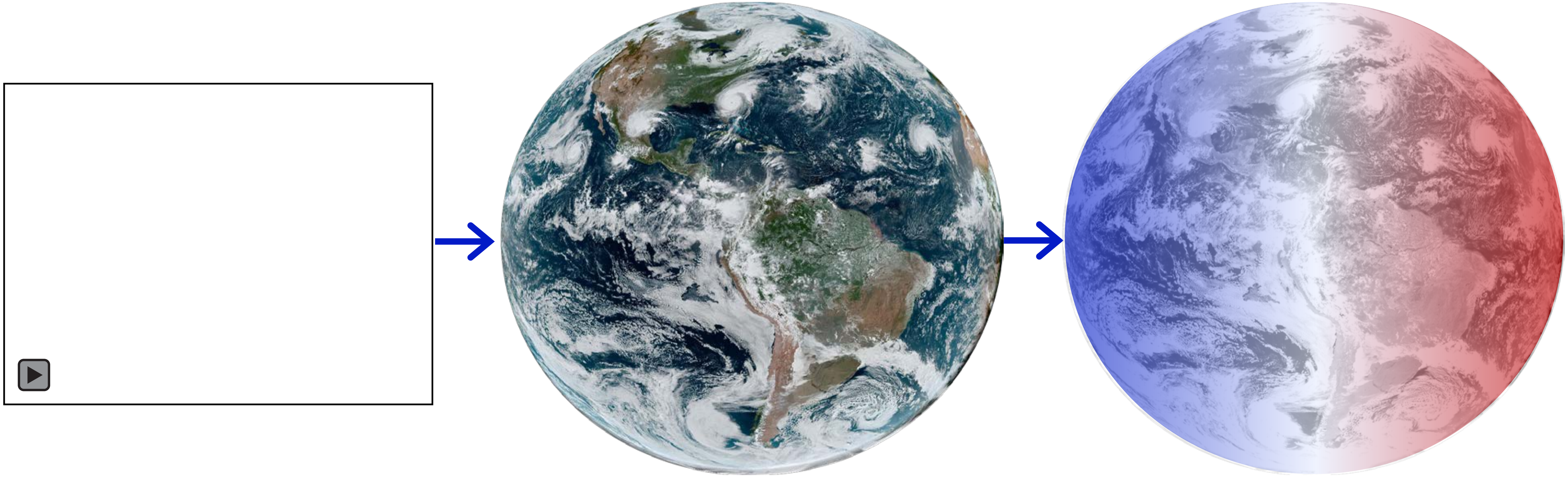
Urban validation: Tewkesbury 2007



CSI = 91%

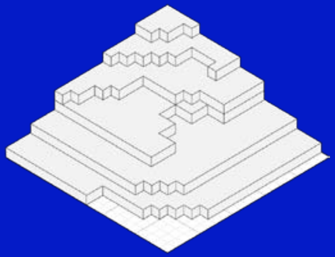
All flooding is local

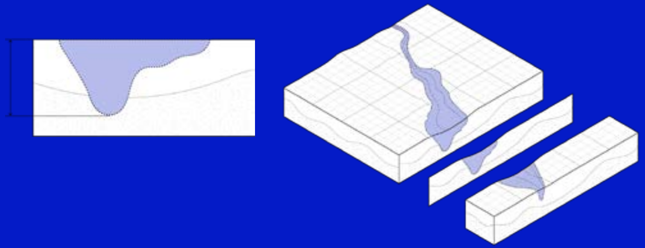
How do we go from local to global?

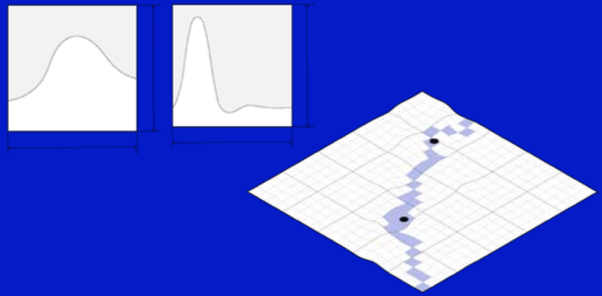


We need models that can be built and executed quickly, at scale.

How do we go from local to global?







Terrain

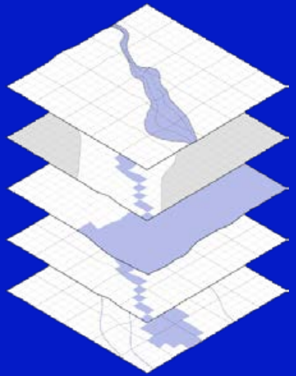
Compile and combine the best available terrain data, including the world-leading FABDEM+ dataset.

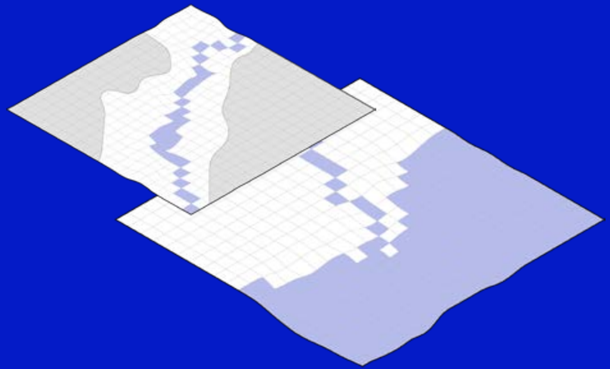
River channels

Model the location and size of all river channels using Fathom's peer-reviewed dynamic Channel Solver.

Defining extremes

Build statistical models from observations that enable the frequency and magnitude of events to be estimated.





Hydrodynamics

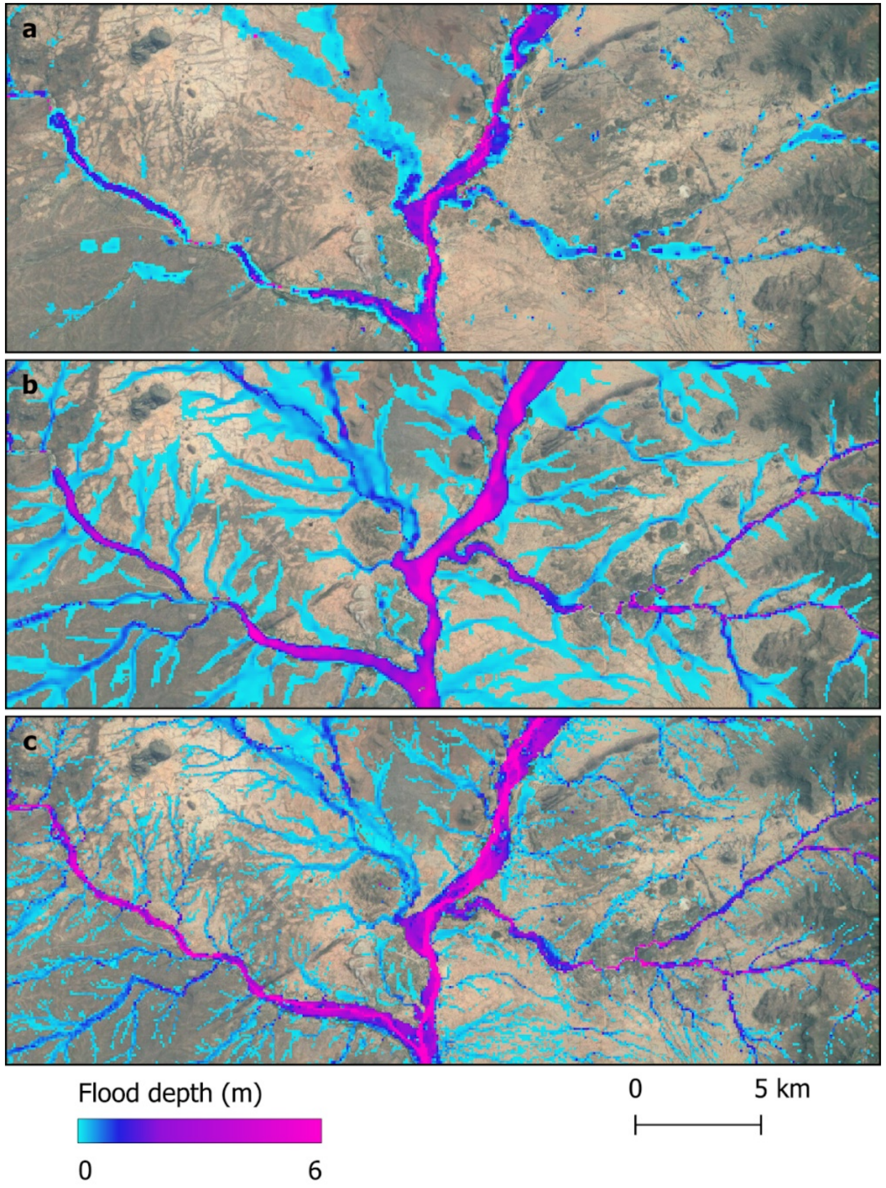
Use pioneering hydrodynamic models to model the propagation of water physically.

Automation

Execute each of the previous steps in an automated model build environment.

Global Flood Models – a rapidly emerging paradigm

Fathom global flood models 2015 to 2023



V1, 2015

V2, 2020

V3, 2023

Sampson et al. (2015). A high resolution global flood hazard model. *Water Resources Research*, **51** (9), 7358–7381. (10.1002/2015WR016954).

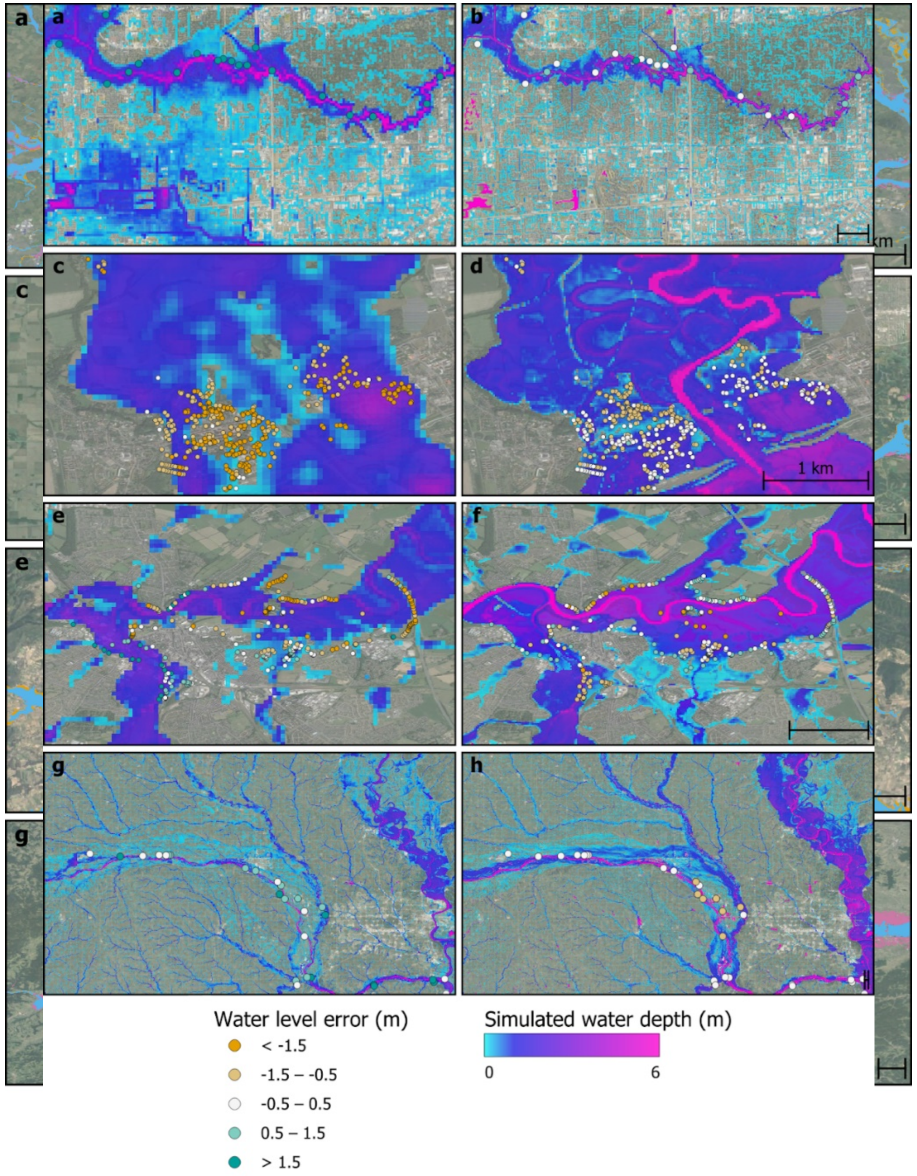
Fathom Global Flood Map 3 validation

National and regional engineering flood hazard maps (US and UK)

Satellite flood images (x2 events)

Post-event reconstructions of maximum flood extent (x4 events)

High water marks (x4 events)

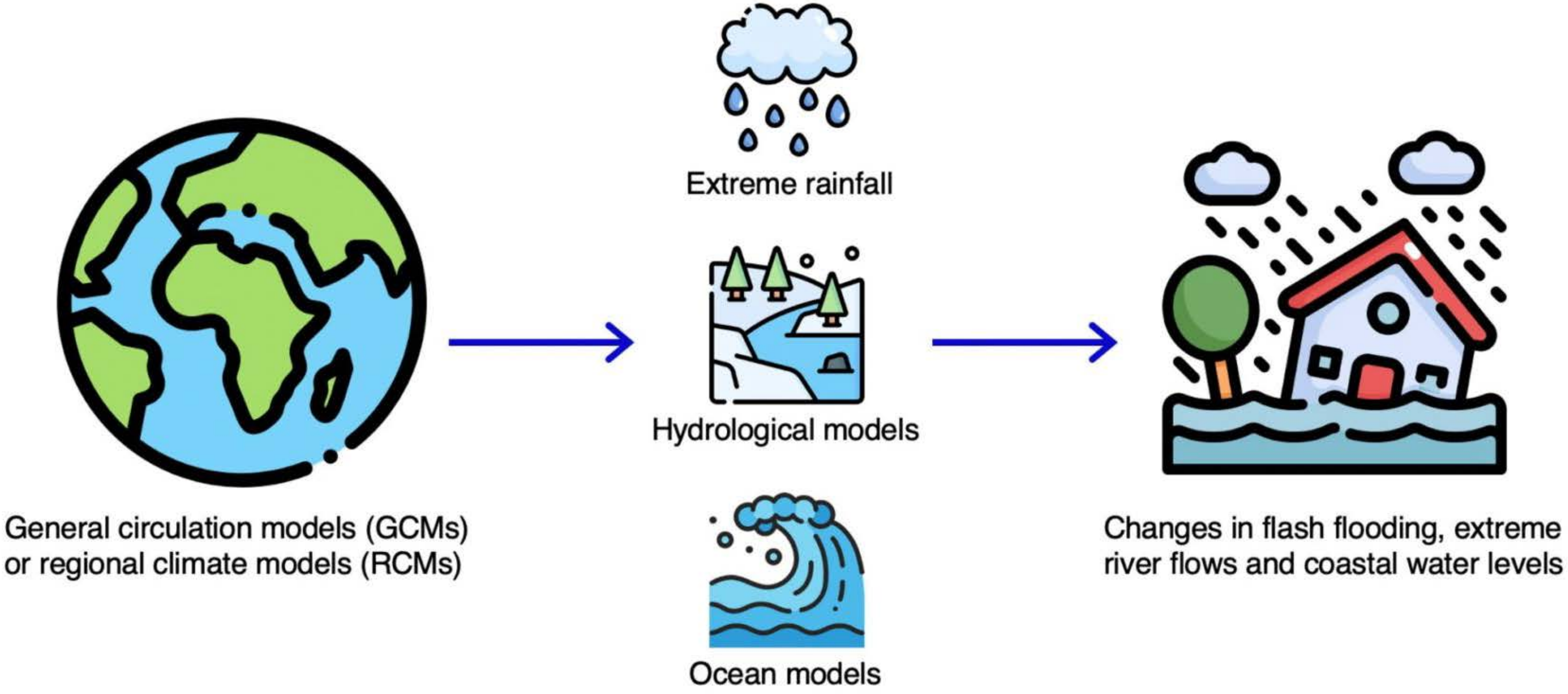


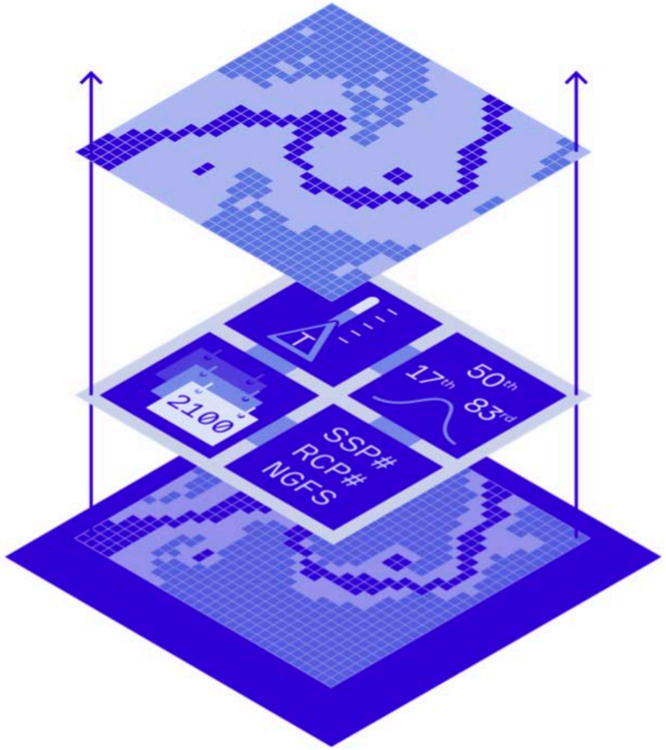
Average performance across all tests

Model	CSI	RMSE (m)
2.0	0.63	1.90
3.0	0.75	0.69
Upper limit for ‘good’ data	~0.8	~0.3-0.5

Wing, O. E. J., Bates, P. D., Quinn, N. D., Savage, J. T. S., Uhe, P. F., Cooper, A., et al. (2024). A 30 m Global Flood Inundation Model for Any Climate Scenario. *Water Resources Research*, *60*(8), e2023WR036460. https://doi.org/10.1029/2023WR036460

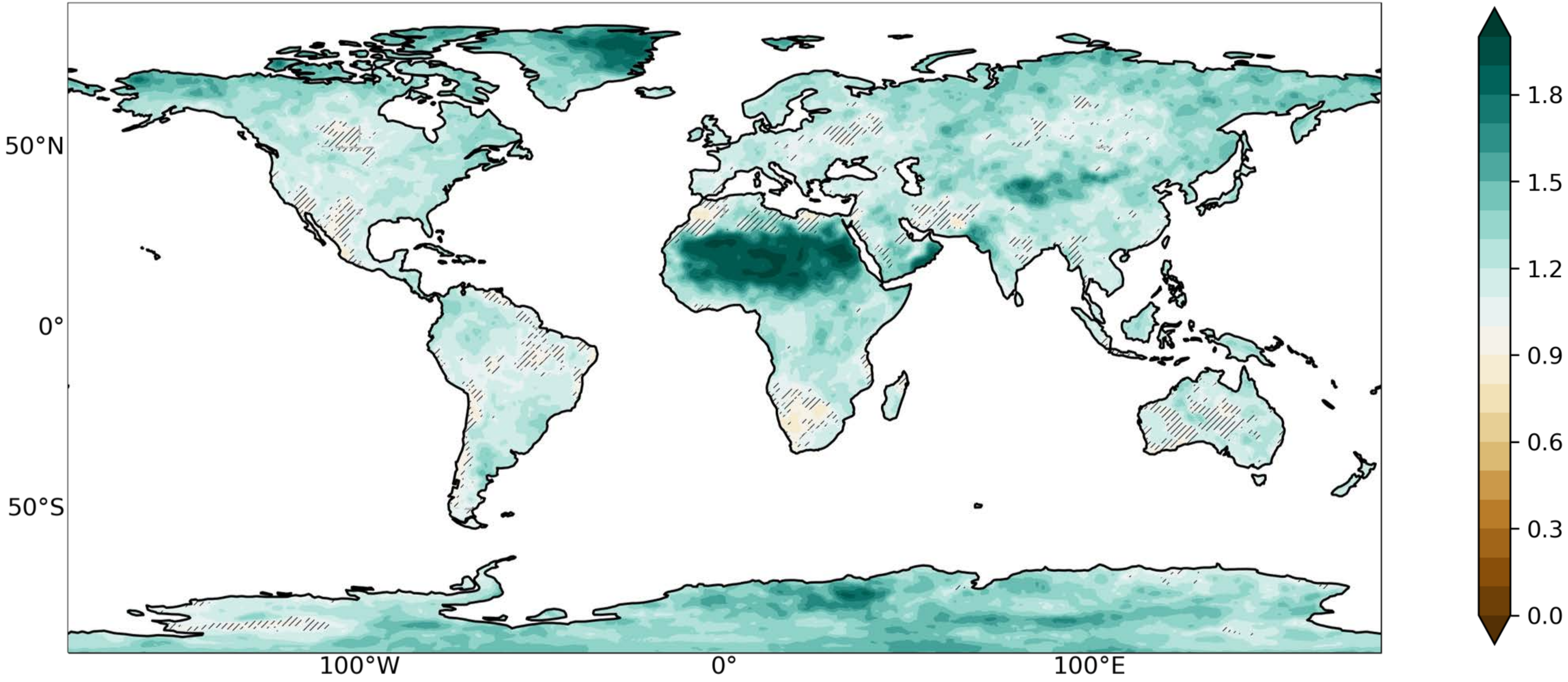
Climate Dynamics





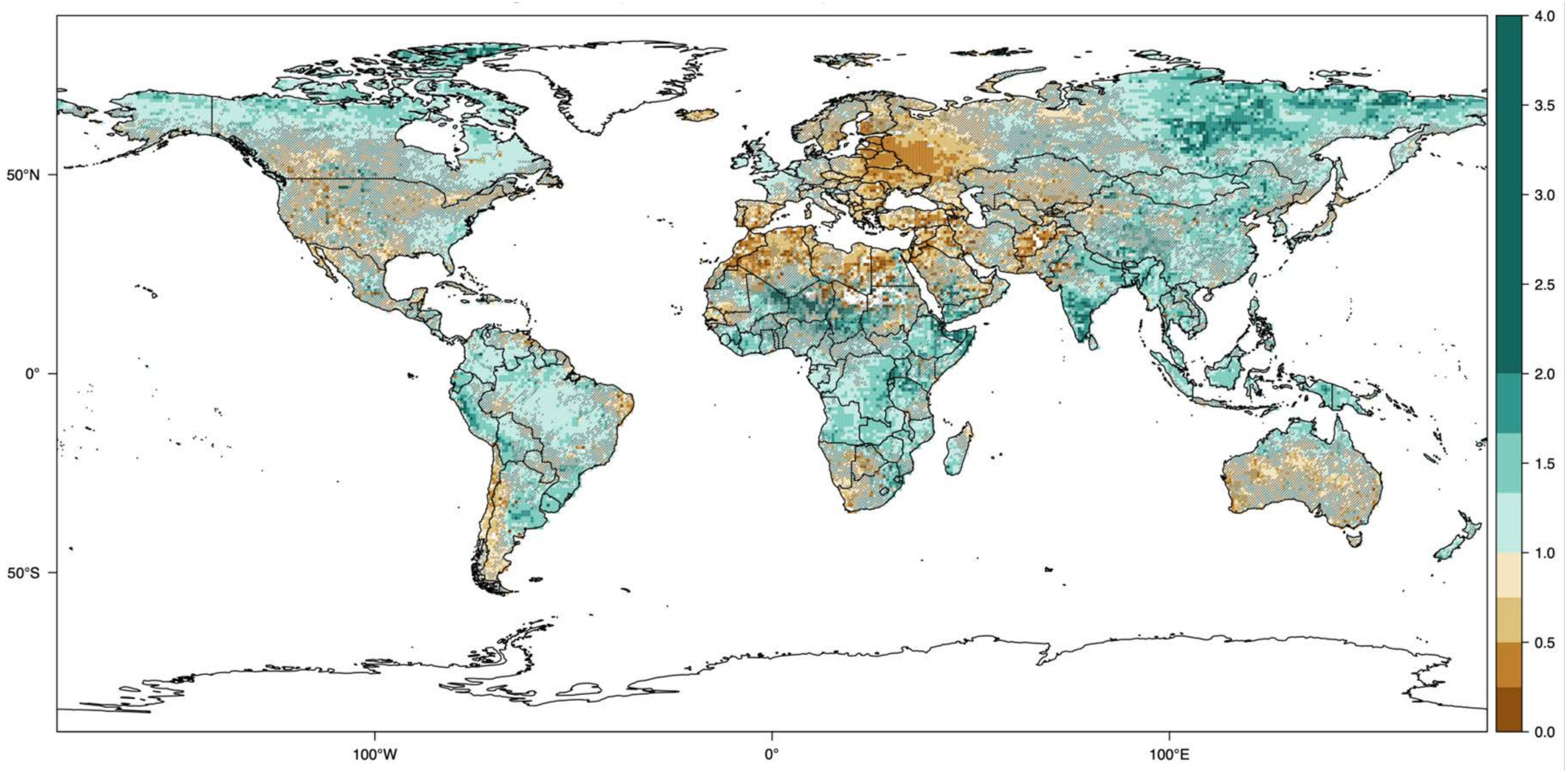
Any scenario
Any flood peril
Anywhere in the world
Compound uncertainty

Pluvial Changes

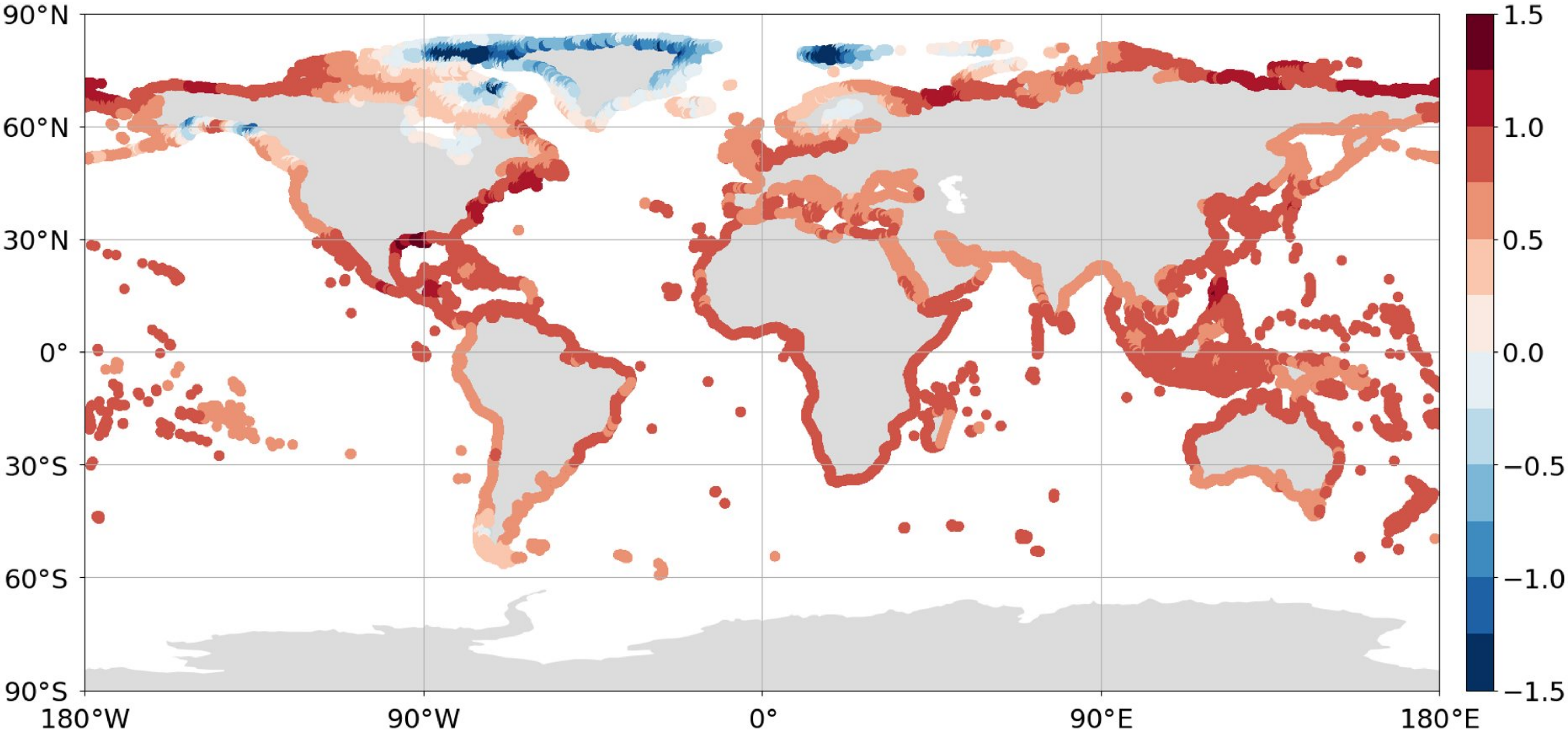


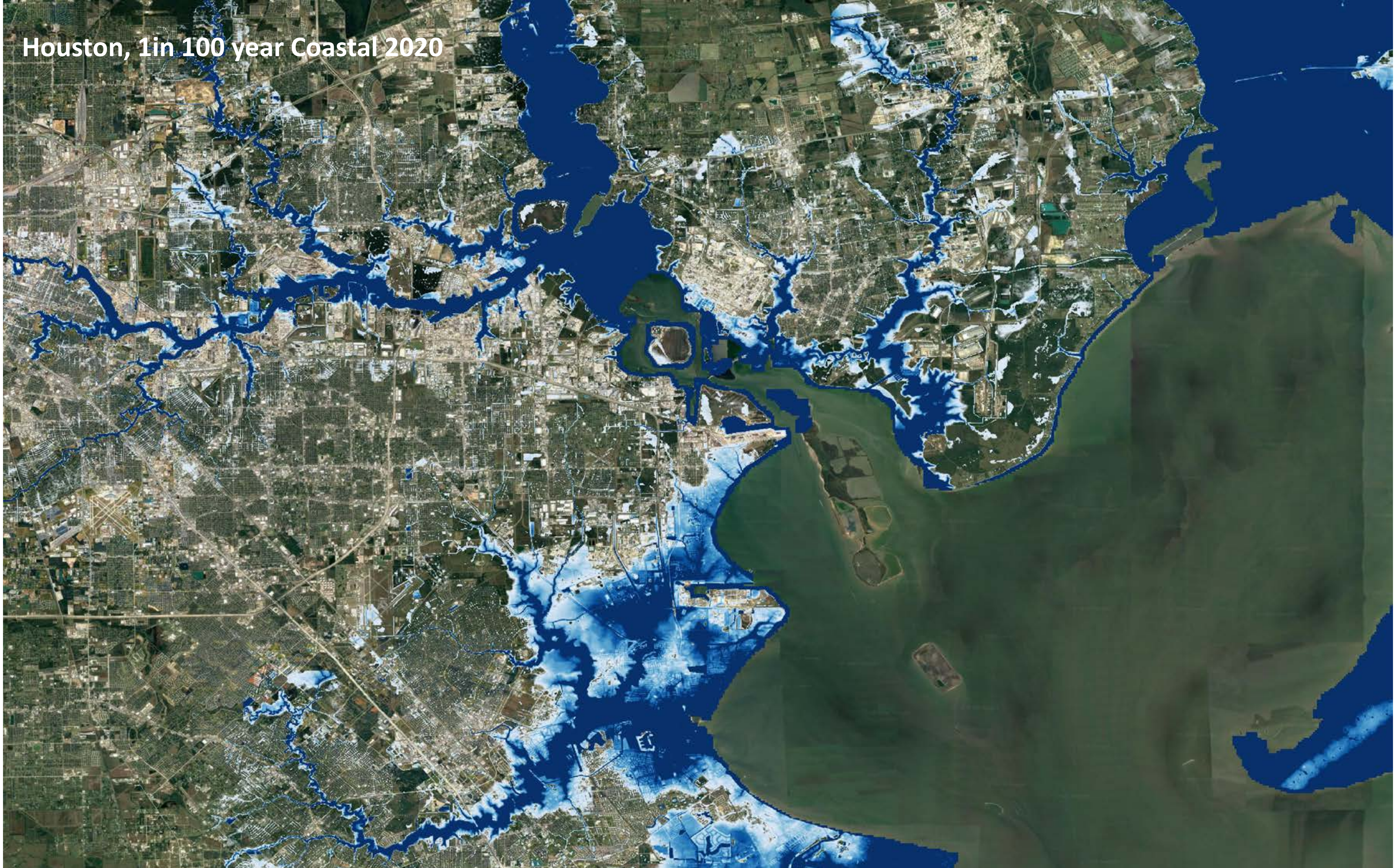
Change factors for precipitation (median of annual max) | GWL = 4 °C | 4 GCMs (median)

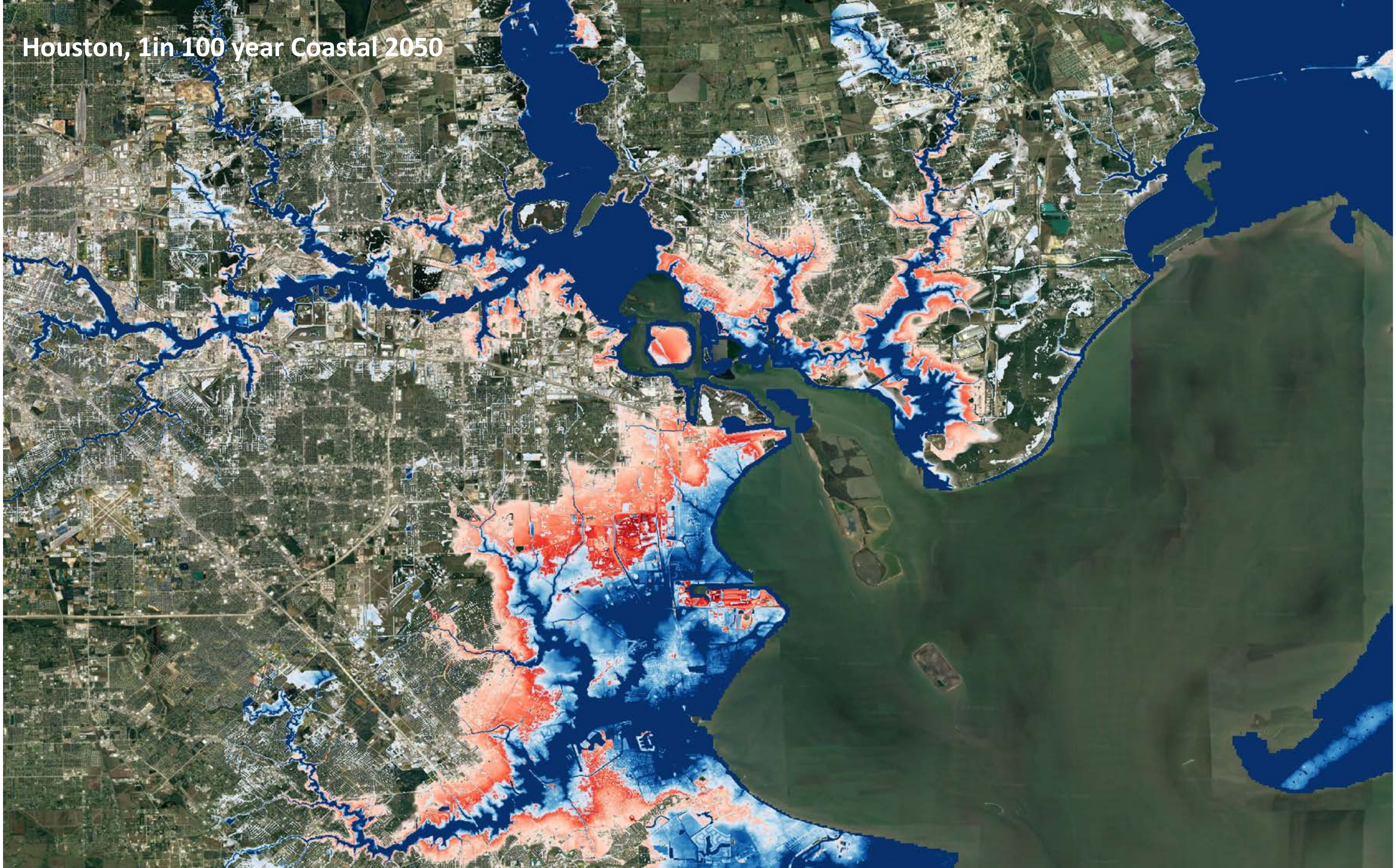
Fluvial Changes



Coastal Changes



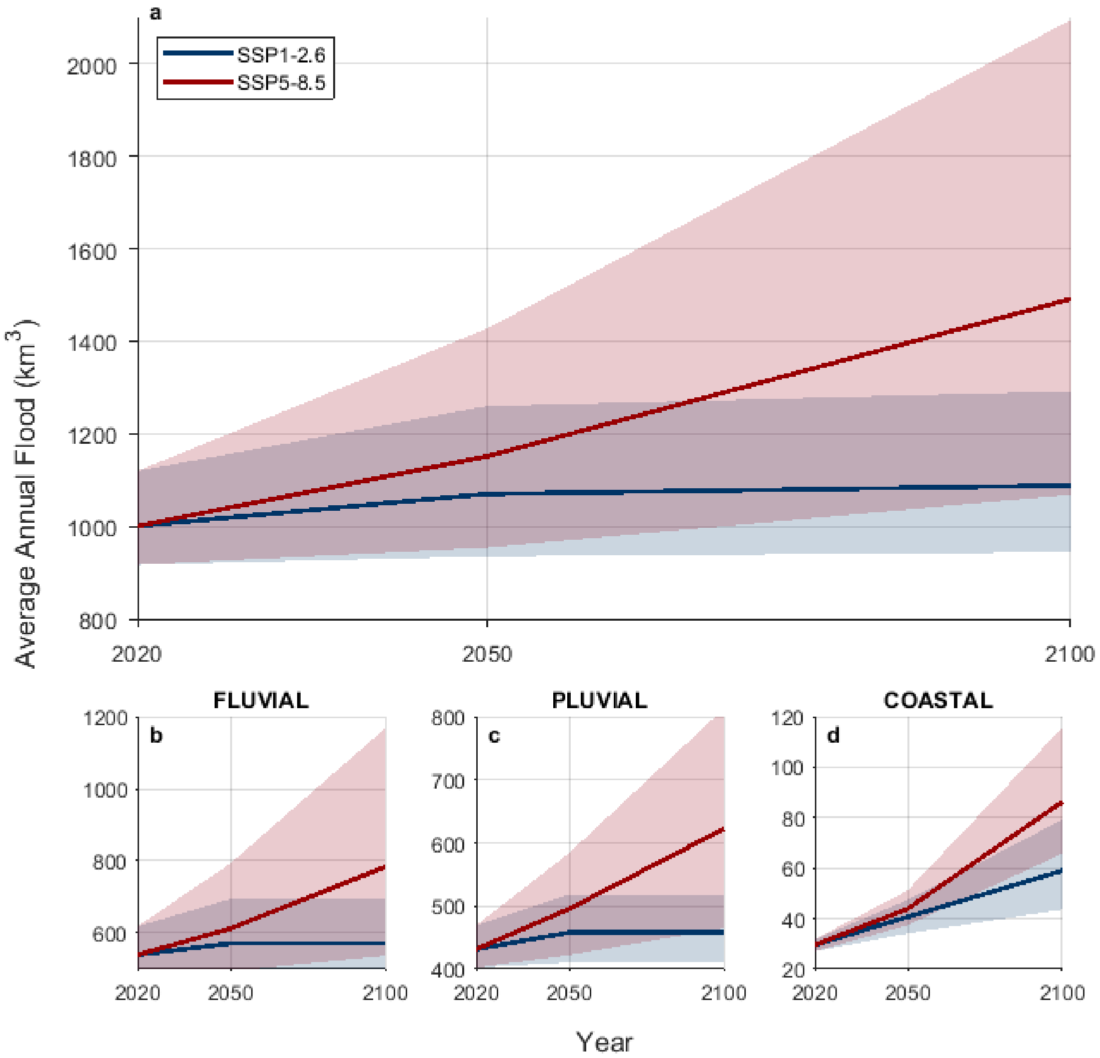

Houston, 1in 100 year Coastal 2020


Houston, 1in 100 year Coastal 2050

Latest projections of global flood hazard

Change in global flood hazard under low (SSP1-2.6) and high (SSP5-8.5) climate scenarios.

Shading represents the likely (66%) range based on climatological uncertainty.



Wing, O., Bates, P., et al. (in review). A 30 m global flood inundation model for any climate scenario. *Water Resources Research*. (10.22541/essoar.169867688.87007201/v1).

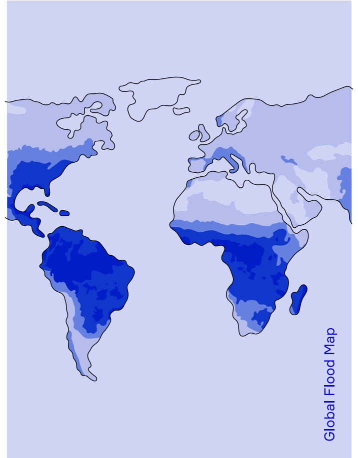
Change in flood hazard

Climate scenario	Median change 2020 - 2100 (%)	Likely range (%)*
SSP1-2.6	9	-6 to +29
SSP5-8.5	49	7 to 109

*Likely uncertainty in characterizing flood hazard in a 2020-centred climate = -8 to +12%

Maps versus models

Maps



Showing what gets wet where...

.. but not what gets wet at the same time.

Static data.

Metrics: Depth by return period.

Individual locations / visualization.

Models

Showing spatially correlated financial losses.

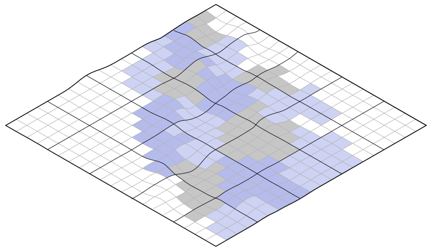
Large numbers of synthetic events.

Software tools.

Metrics: AAL, standard deviation, loss for each event, loss exceedance probability.

Portfolios / quantification.

From hazard to risk



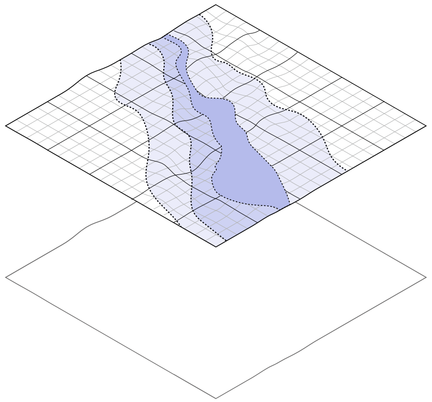
01

Event set

Spatial extent of events

— Characterized by size, location, and return period of flooding per grid cell.

— Millions of events representing 10,000 years of activity.



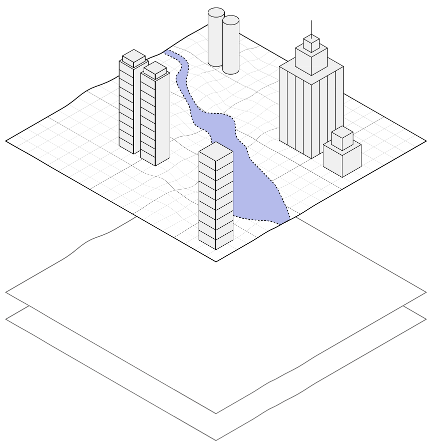
02

Hazard

Physical intensity for each location for each event

— A flood footprint represents flood depth for each grid cell for each event.

— Used to represent the varying impact and intensities of one event on different locations.



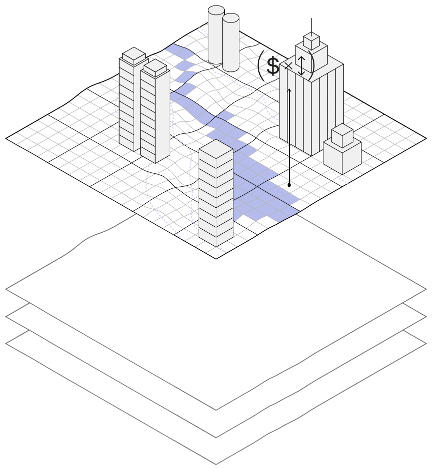
03

Exposure

Global asset value distributions

— Spatial distribution of asset values and building heights.

— For residential, commercial and industrial assets.



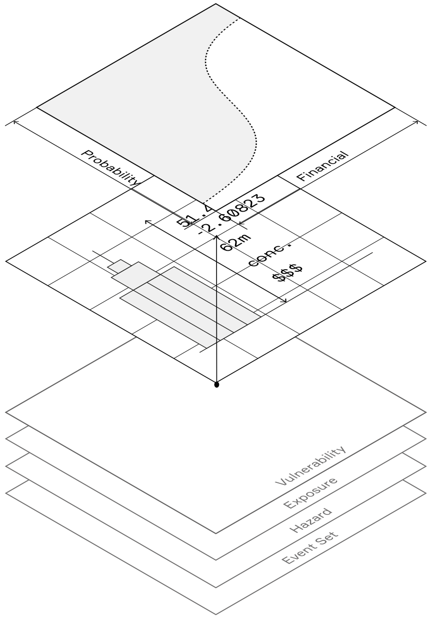
04

Vulnerability

Relating hazard to damage per asset type

— Links the hazard metric to a damage ratio.

— Quantifies the extent of damage to a building caused by an event, based on the characteristics expressed within the exposure dataset.



05

Financial module

Calculating a range of loss metrics for different financial perspectives

— Calculates losses based on conditions provided by the user.

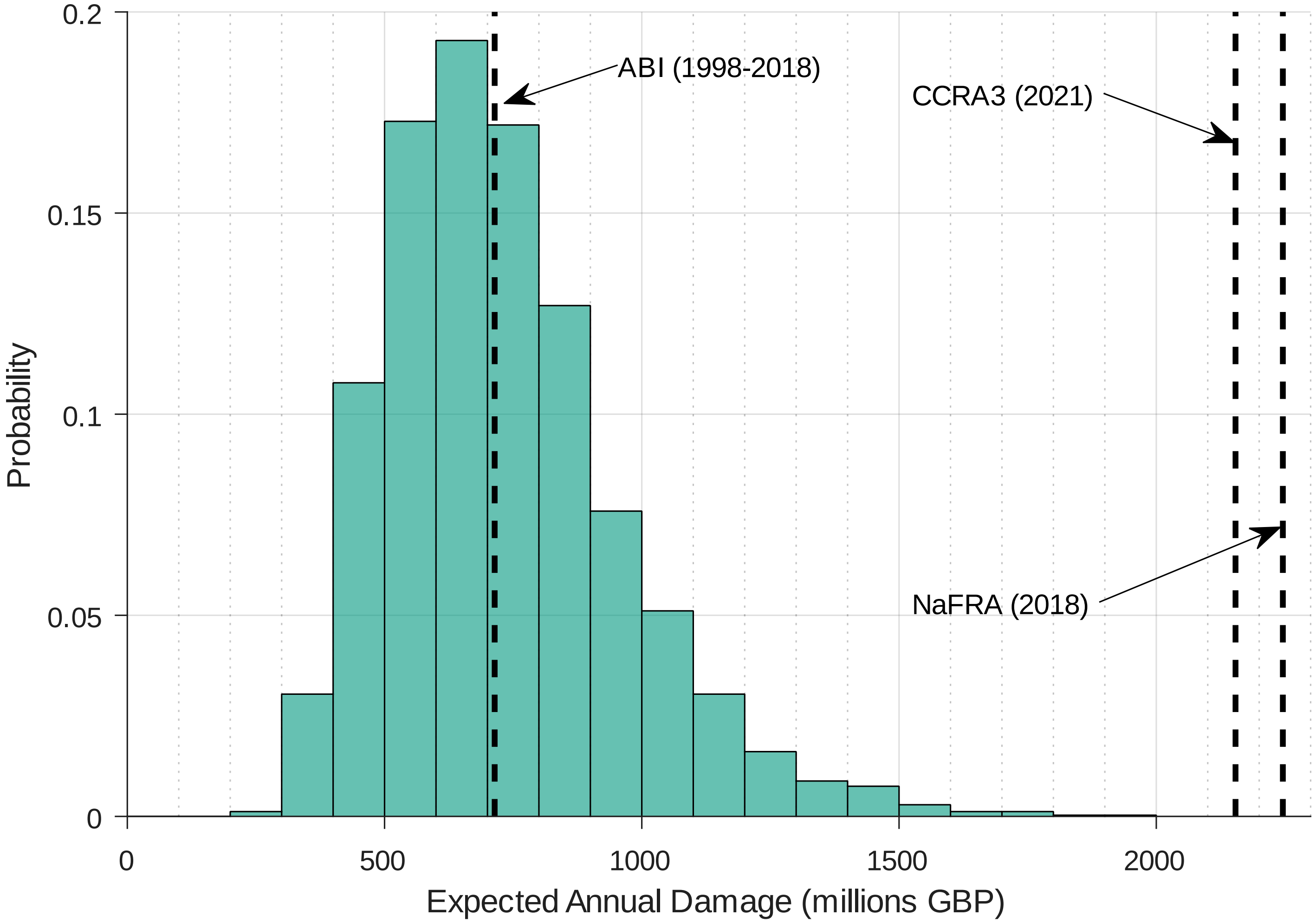
— Produces a loss table for every simulated event within each year for the user's portfolio. Metrics, such as loss exceedance probabilities and average annual loss can be calculated from this for different perspectives and output resolutions.

Expected Annual Damage estimates

Observed EAD: £714M

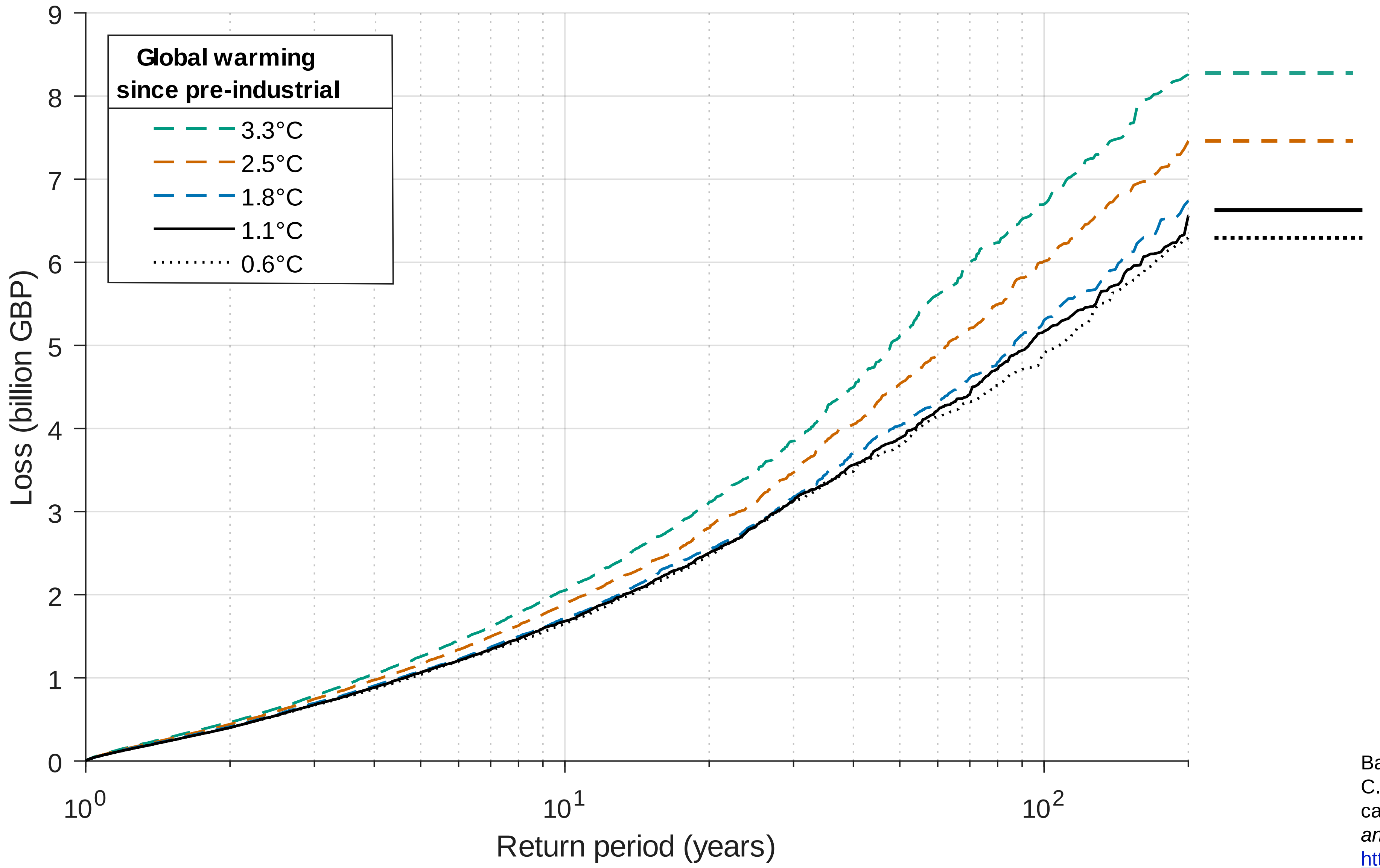
Modelled EAD: £730M

Simulated EAD from 10,000 random samples of cat model 20-year time periods compared to past estimates



Bates, P. D., Savage, J., Wing, O., Quinn, N., Sampson, C., Neal, J., & Smith, A. (2023). A climate-conditioned catastrophe risk model for UK flooding. *Natural Hazards and Earth System Sciences*, *23*(2), 891–908. https://doi.org/10.5194/nhess-23-891-2023

Loss exceedance curves under climate change



Bates, P. D., Savage, J., Wing, O., Quinn, N., Sampson, C., Neal, J., & Smith, A. (2023). A climate-conditioned catastrophe risk model for UK flooding. *Natural Hazards and Earth System Sciences*, *23*(2), 891–908. https://doi.org/10.5194/nhess-23-891-2023

Conclusions

Increasingly, actuaries also need to be data scientists, using information from numerical and Machine Learning models

Risk has changed, and will change further

- There is considerable value in using forward-looking models to provide clients with more robust advice

For floods, recent numerical and data developments are transforming our ability to assess current and future risks under non-stationarity

Actuaries stand to play a key role in the adoption and use of these emerging tools, with the power to drive real change in their organizations

But … models are complex and their outputs uncertain

- Need to carefully understand their strengths and weaknesses, and the limits to prediction
- Need to insist on transparent and independent peer-review
- Need to be very cautious about accepting ‘black boxes’

White paper

Navigating global flood risk in a non-stationary world – A primer for actuaries

White paper available here:

https://www.fathom.global/insight/navigating-flood-risk-primer-for-actuaries/

Questions

Comments

Expressions of individual views by members of the Institute and Faculty of Actuaries and its staff are encouraged.

The views expressed in this presentation are those of the presenter.