

Limits to natural disasters management: the influence of human behavior

See also:

<https://www.youtube.com/watch?v=vt-xS3MOPZ0>

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IVM Institute for
Environmental Studies



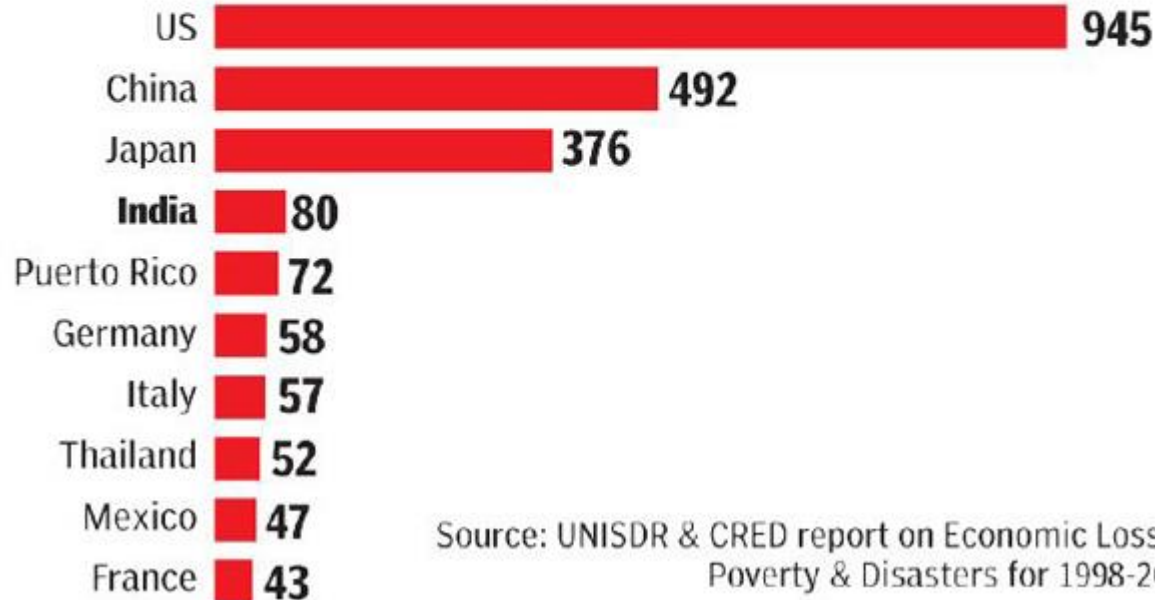
Natural disasters kill on average **60,000 people** per year

Source: ourworldindata.org / EM-DAT

US TOPS LIST IN DISASTER LOSSES

Top 10 countries in disaster losses: 1998-2017

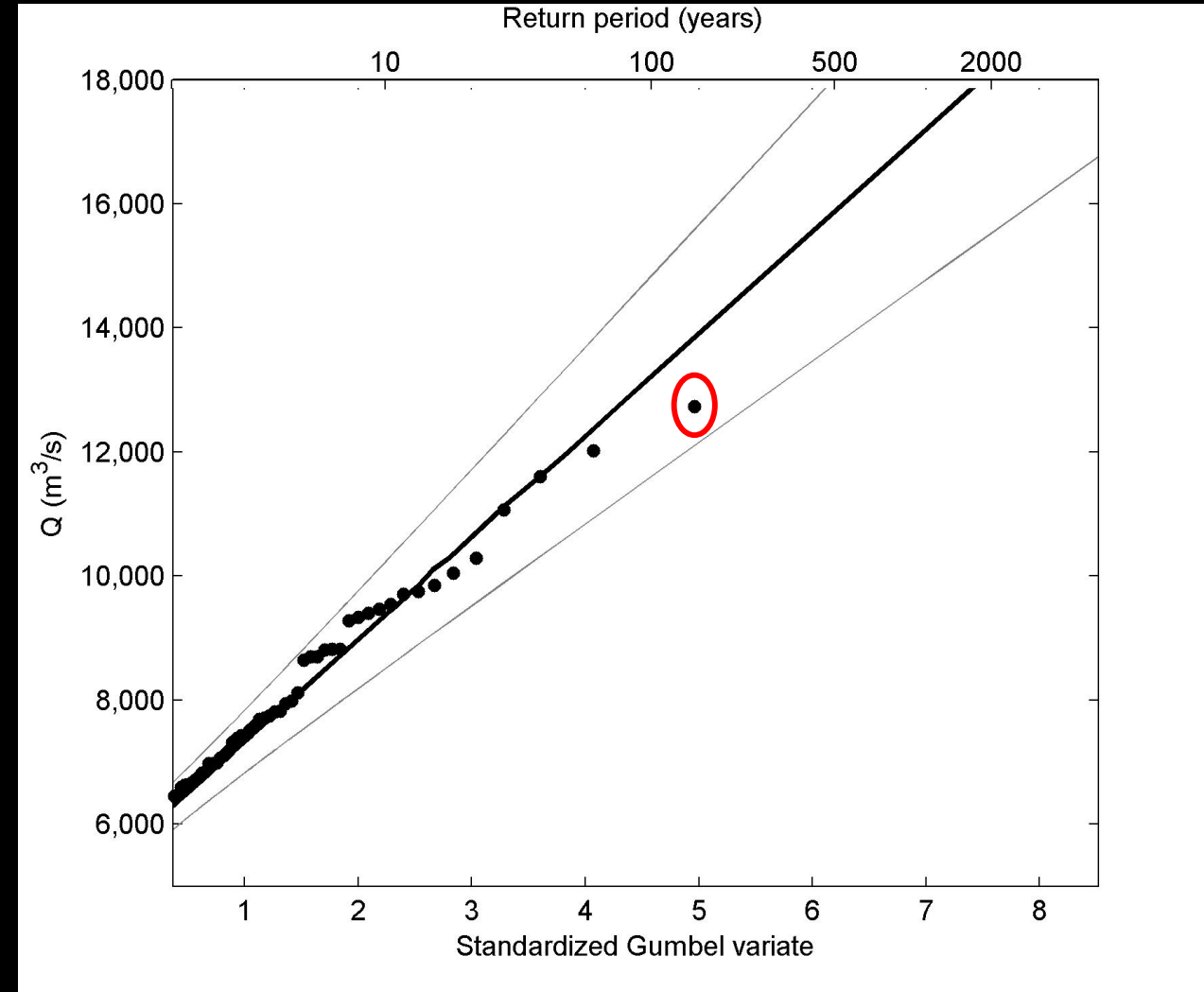
Losses (In billion \$)



Source: UNISDR & CRED report on Economic Losses, Poverty & Disasters for 1998-2017

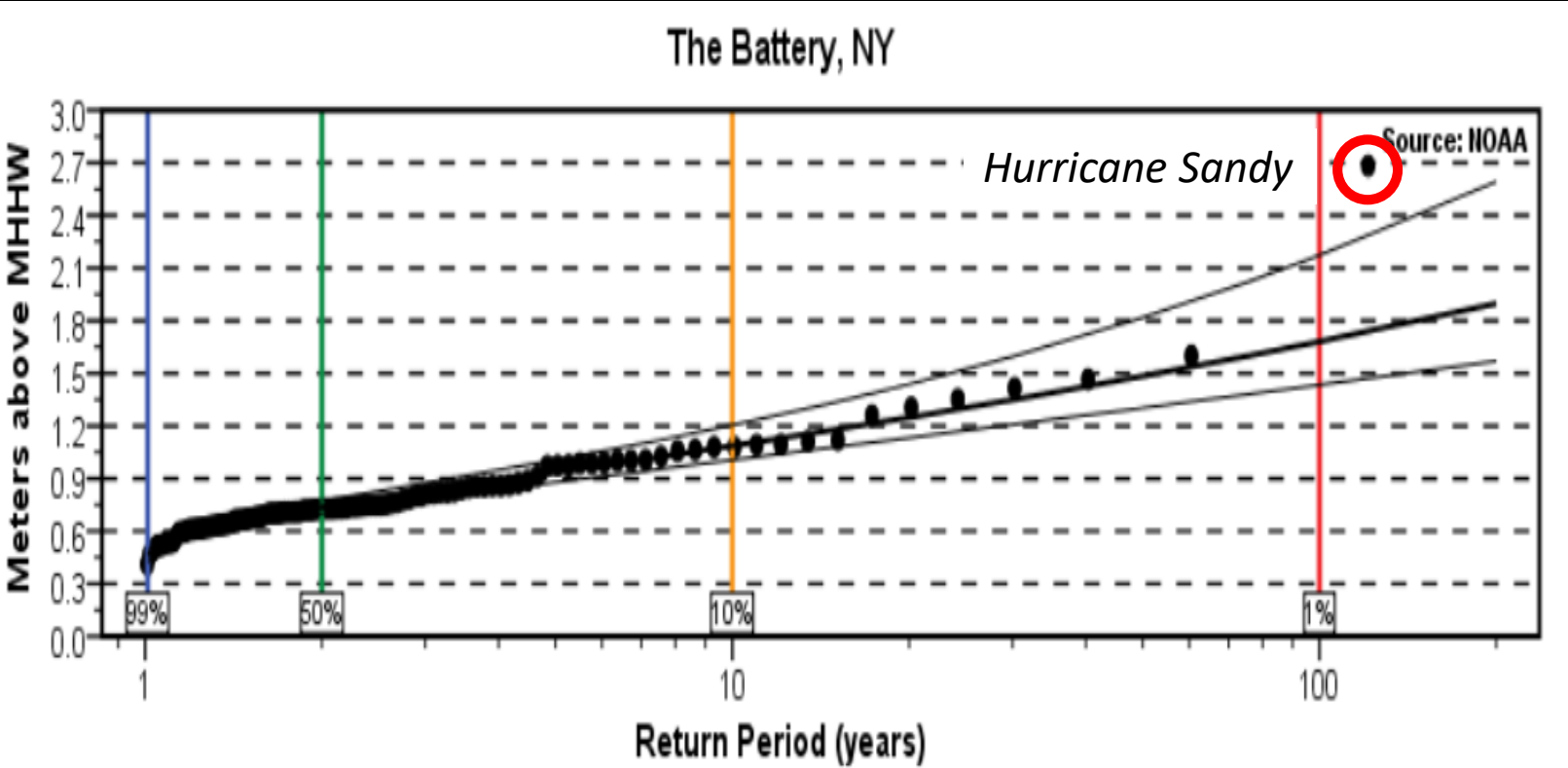
When focusing on **extreme events** we often use statistical methods such as **Extreme Value analysis**

Here an example of extrapolating annual peak discharges for the river Rhine near station Lobith, using historical data

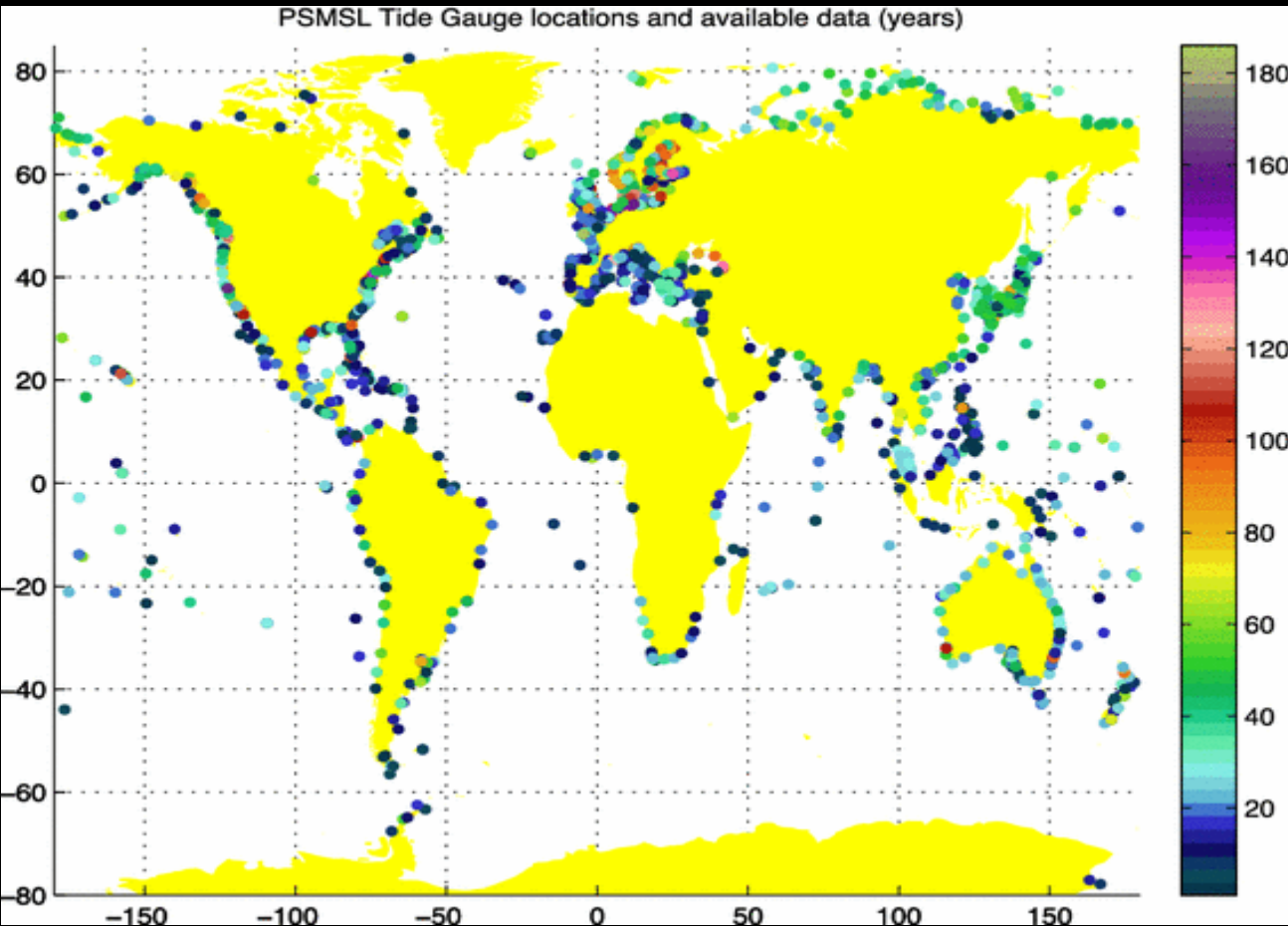


River Rhine: Annual discharge maximum at Station Lobith

However, extrapolating historic annual maximum **water levels** (such as here for NYC 1850 – current), does not always provide good estimates of extreme, low probability events. The example shows that extreme water level due to Hurricane Sandy fall way out of the confidence interval



Tide gauge Station The Battery, NY



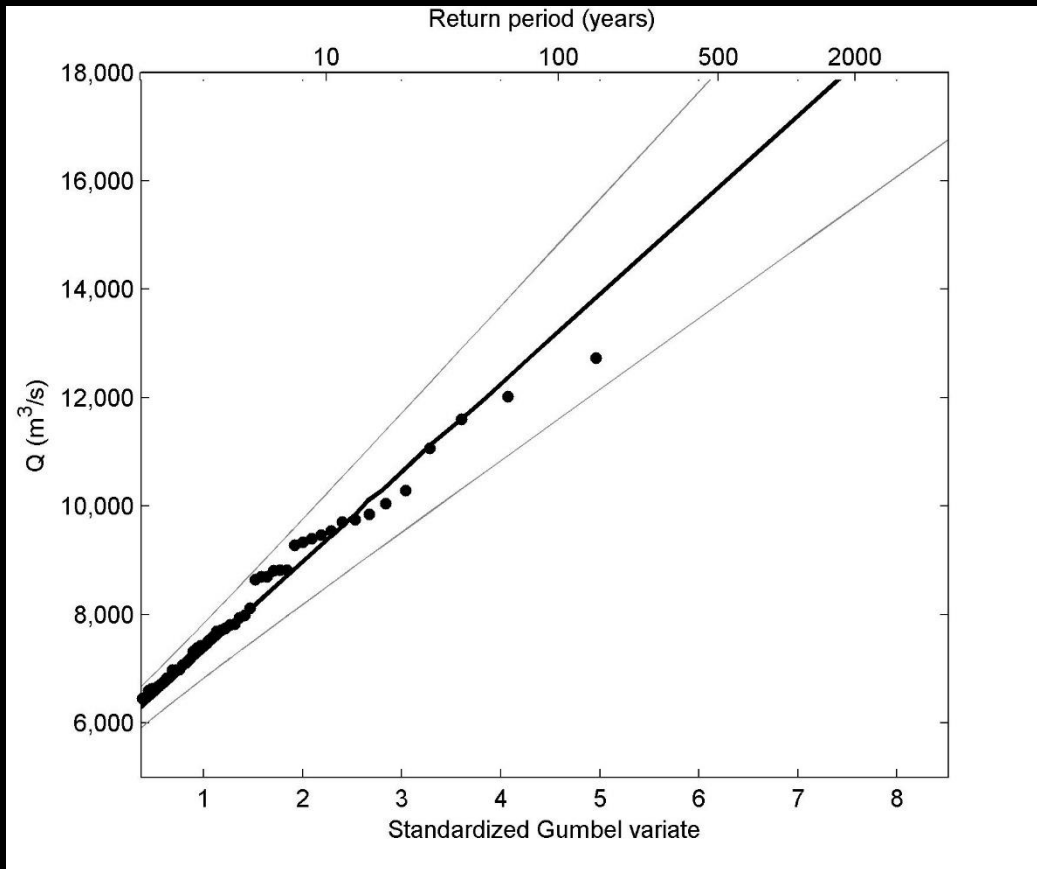
Cipollini et al., 2017; Surveys in Geophysics

One reason for such misfit of capturing extremes in statistical methods is the lack of data. For example, this map shows the limited number of coastal gauging stations:

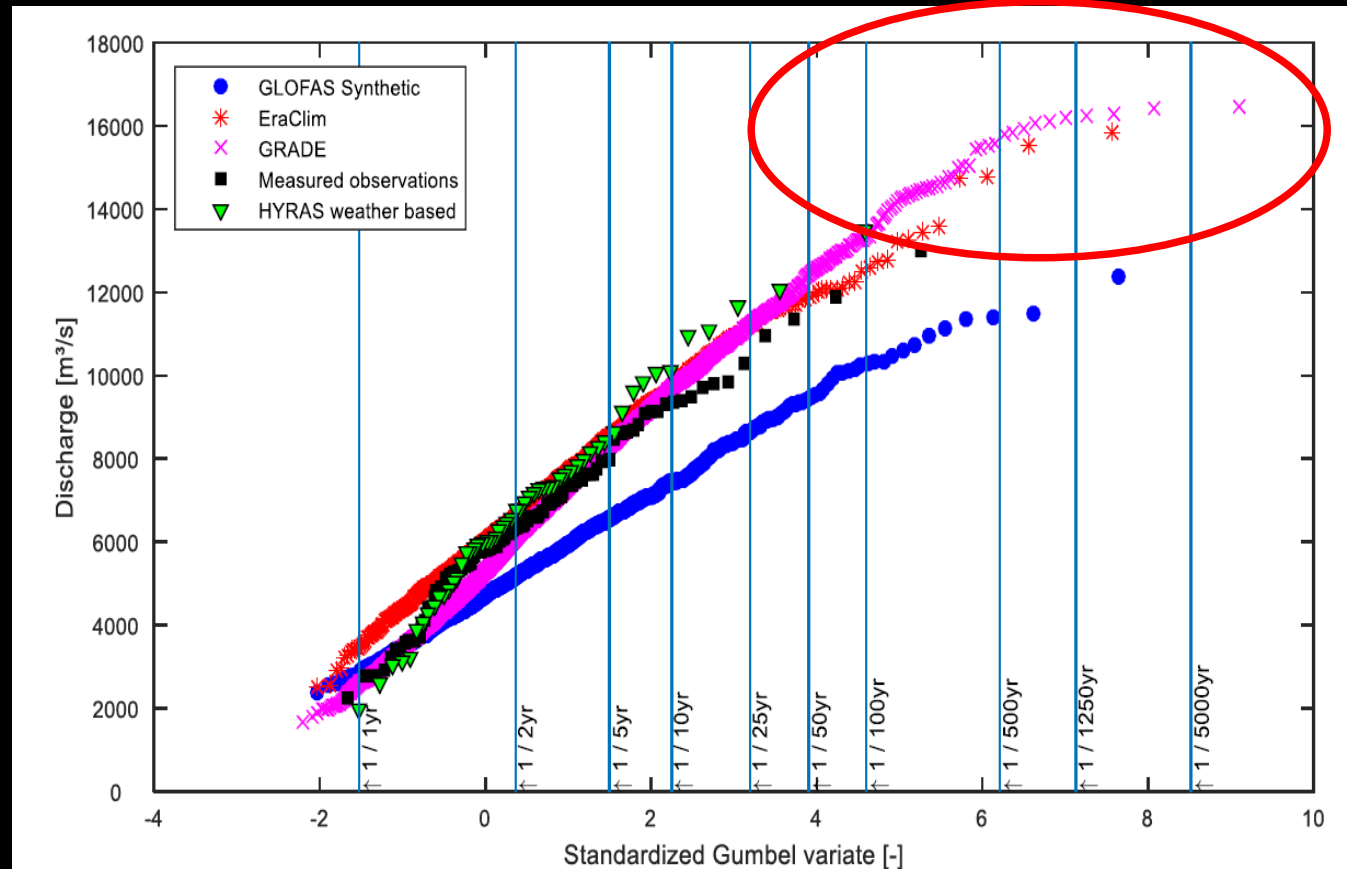
data series of only 30 years lead to uncertainties in predicting low probability events

One way to extend the historical database is to use simulation models. Here an example for the river Rhine where we simulated extreme discharges using different models and different climate data sets. However, the **non linear behavior** at the **tails** of the distribution can not only be explained by physical factors such as climate or geomorphology.

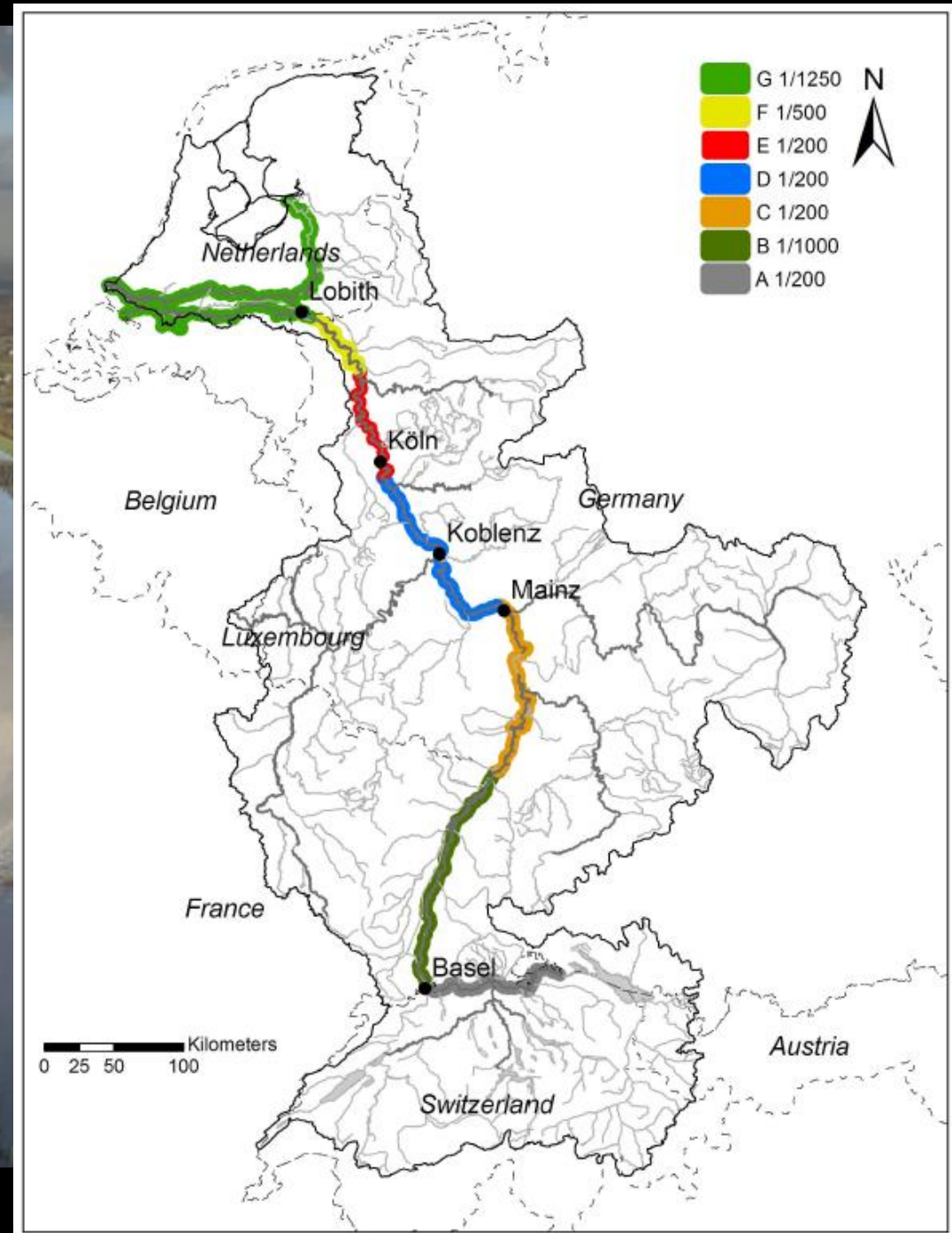
Observed max. annual discharges Rhine river



Observed + modeled max. annual discharges Rhine river



Differences at the tails can be largely attributed to **human factors**: the Flood protection standards upstream from Lobith are lower than downstream. This causes massive flooding above a certain threshold discharge



A key question is: why are the protection standards different along the river Rhine? For this to be answered, we need to know:

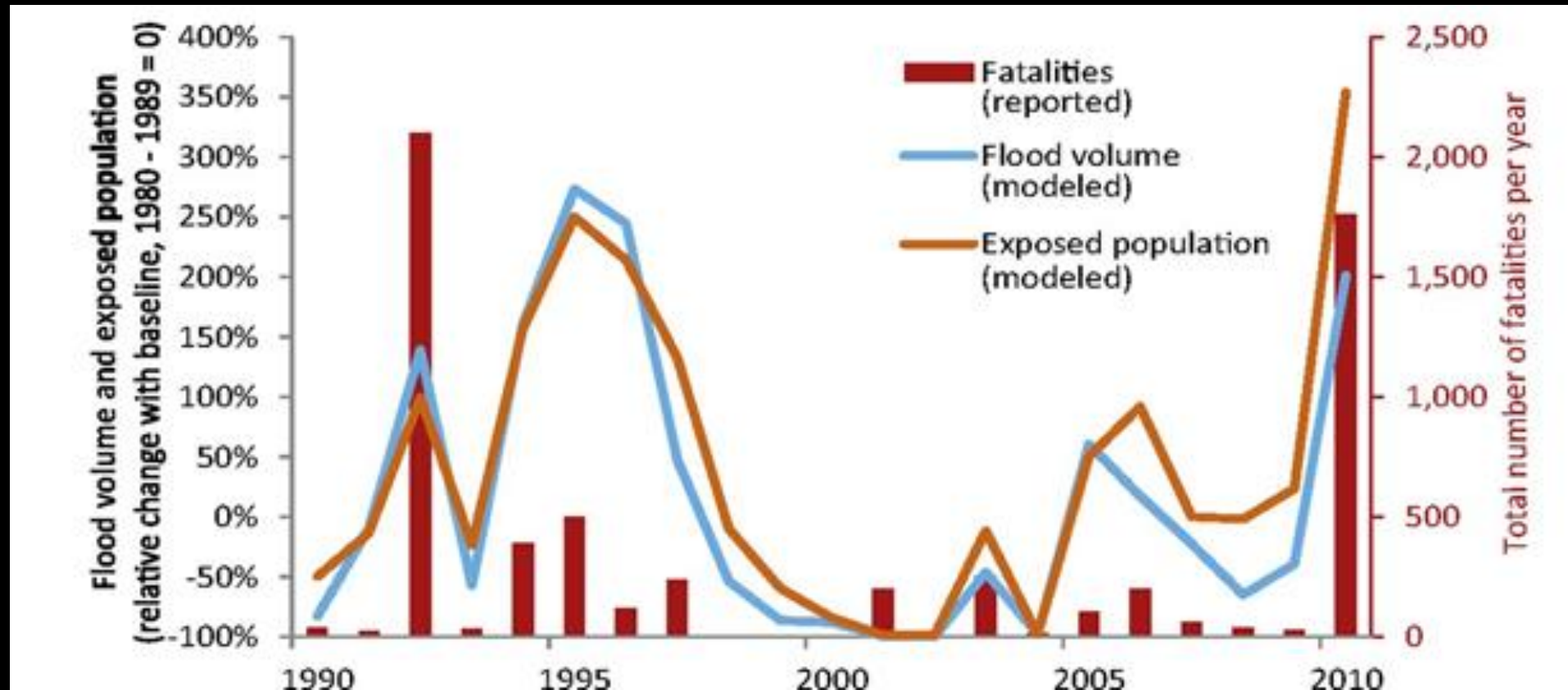
How do people **react** to **extremes**?

What is the influence of **behavior dynamics** on flood adaptation?

Will factors drive **adaptive behavior**?

One of the key driver for human adaptation is **risk perception**. This graph shows the number of fatalities in Pakistan (Indus river). It shows high fatalities in 1993. However, in a even higher flood in 1995, fatalities were much lower

Pakistan floods 1990-2010

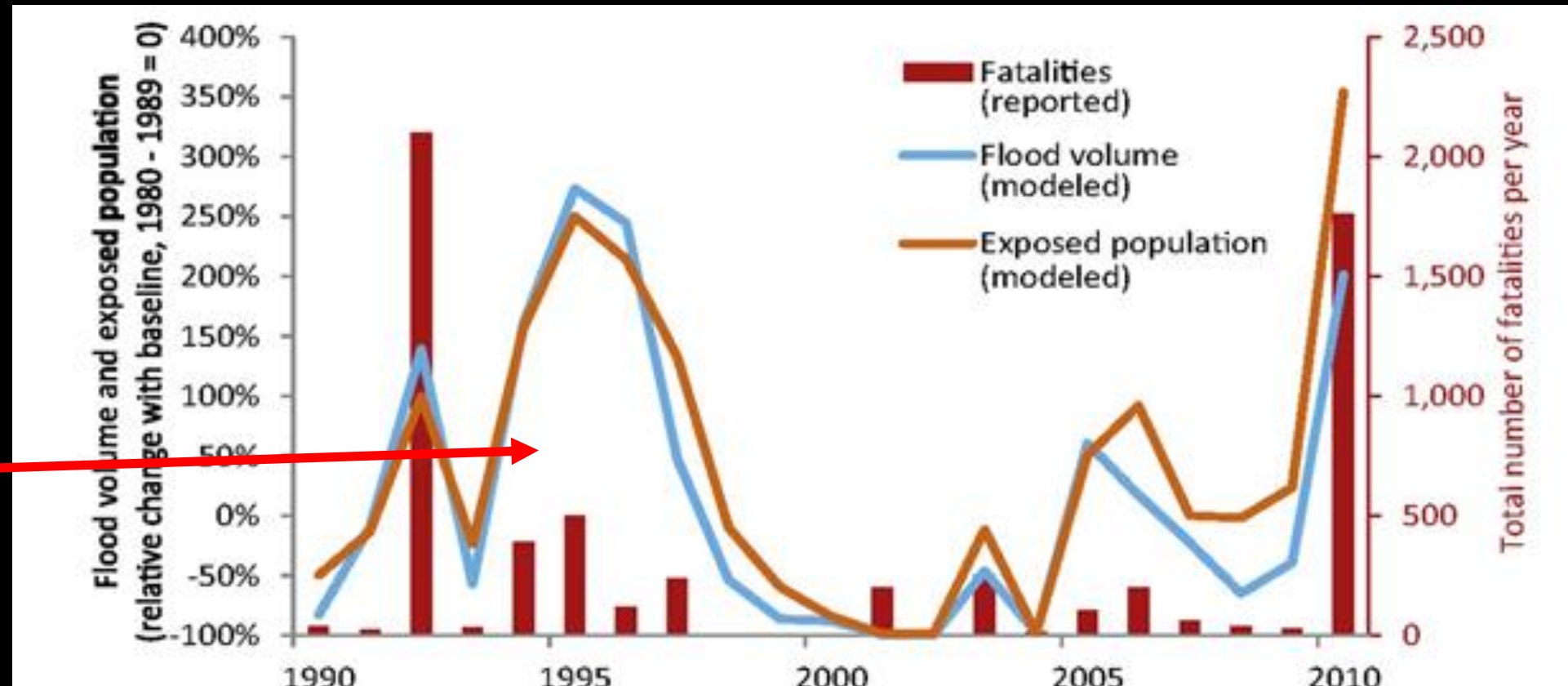


Jongman et al. 2015, PNAS

This difference in fatalities can only be explained by human factors: Due to the experience of 1993, people have relocated, installed improved protection or early warning measures. In other words, the flood of 1993 raised risk perception and a sense of urgency that has led to increased adaptation. This paradox is called “**The adaptation effect**” (Di Baldesarre et al., 2018; Aerts et al., 2018)

Pakistan floods 1990-2010

People relocated?
Better measures?
Destructed houses
were not rebuild?



Jongman et al. 2015, PNAS

Such paradoxes
have been first
described by Gilbert
White

- **Adaptation** effect
- **Levee** Effect

And have seen a revival in the
new research area of Socio-
hydrology

Di Baldessarre et al., 2018; HESS

The University of Chicago

HUMAN ADJUSTMENT TO FLOODS

A GEOGRAPHICAL APPROACH TO THE FLOOD PROBLEM IN THE UNITED STATES

A DISSERTATION SUBMITTED TO THE FACULTY
OF THE DIVISION OF THE PHYSICAL SCIENCES
IN CANDIDACY FOR THE DEGREE OF DOCTOR
OF PHILOSOPHY

DEPARTMENT OF GEOGRAPHY

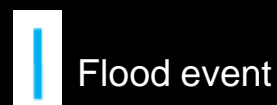
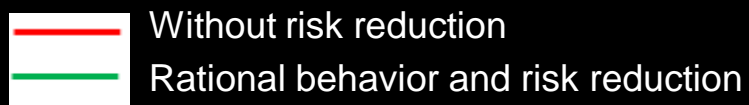
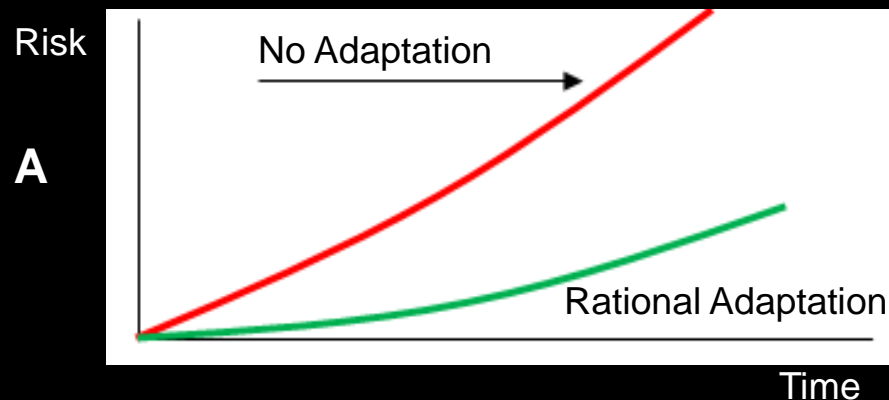
JUNE, 1942

Research Paper No. 29

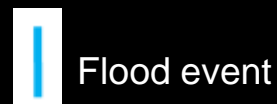
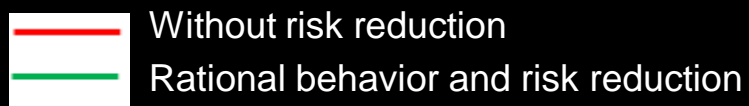
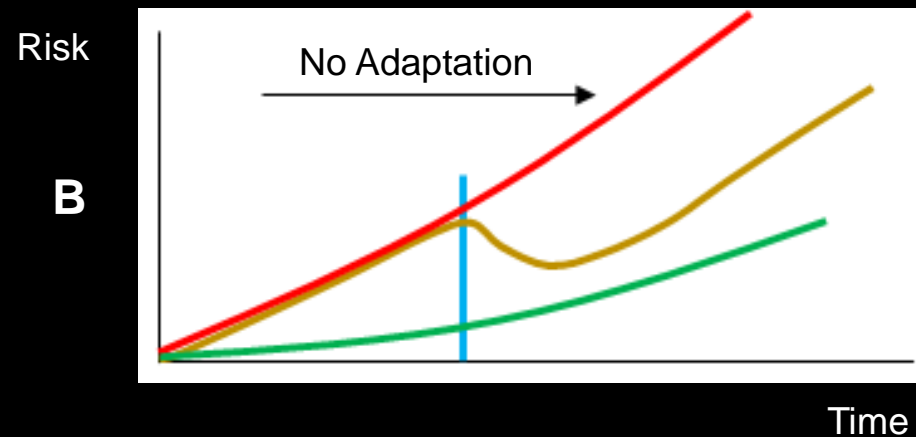
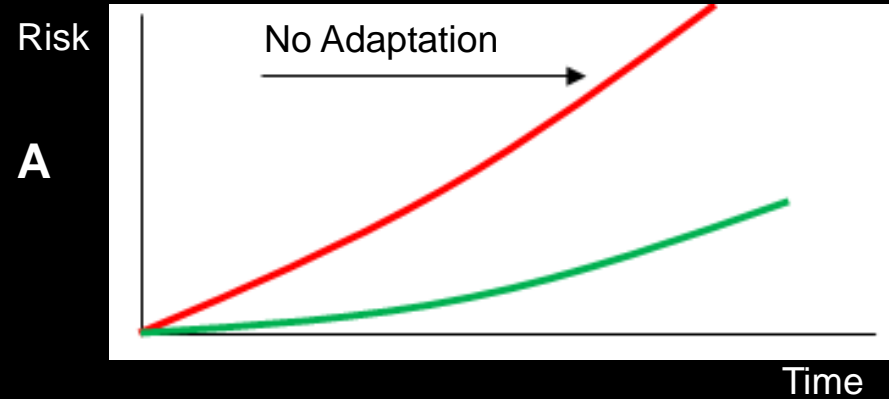
By

GILBERT FOWLER WHITE

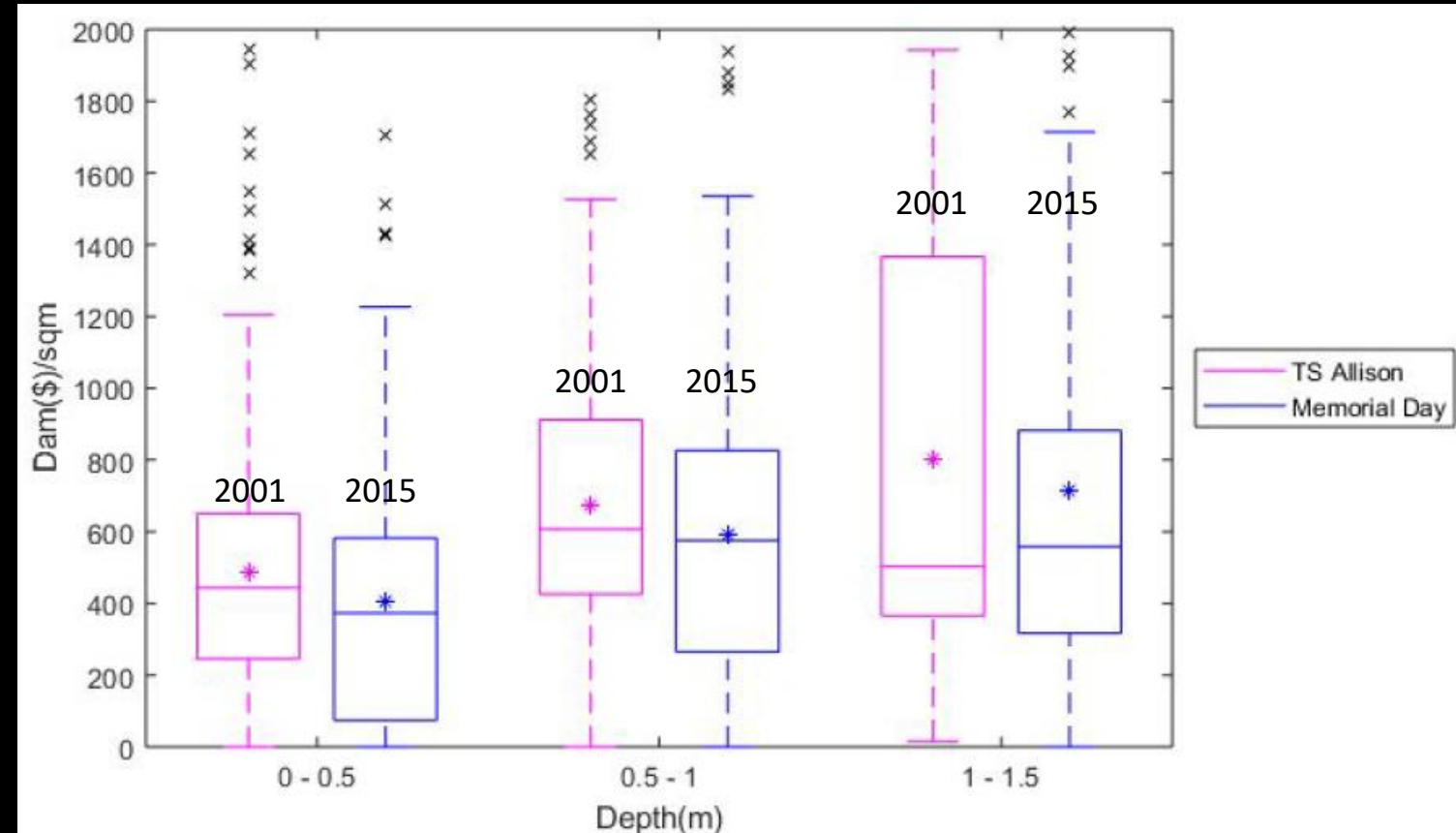
The **Adaptation** effect shows the effect of 'rational-' and 'bounded rational-' behaviour. When resources are available, a rational flood manager would invest in protection as risk increases (e.g. due to climate change or urbanization). The green curve show rational behaviour, and risk is only increasing slowly over time



In reality however, decision makers tend to behave ‘bounded rational’ (brown curve): they only invest in flood adaptation measures right after an extreme event because risk perception is high. After a while, perception fades away, investments in flood adaptation decrease, and risk start to increase again.

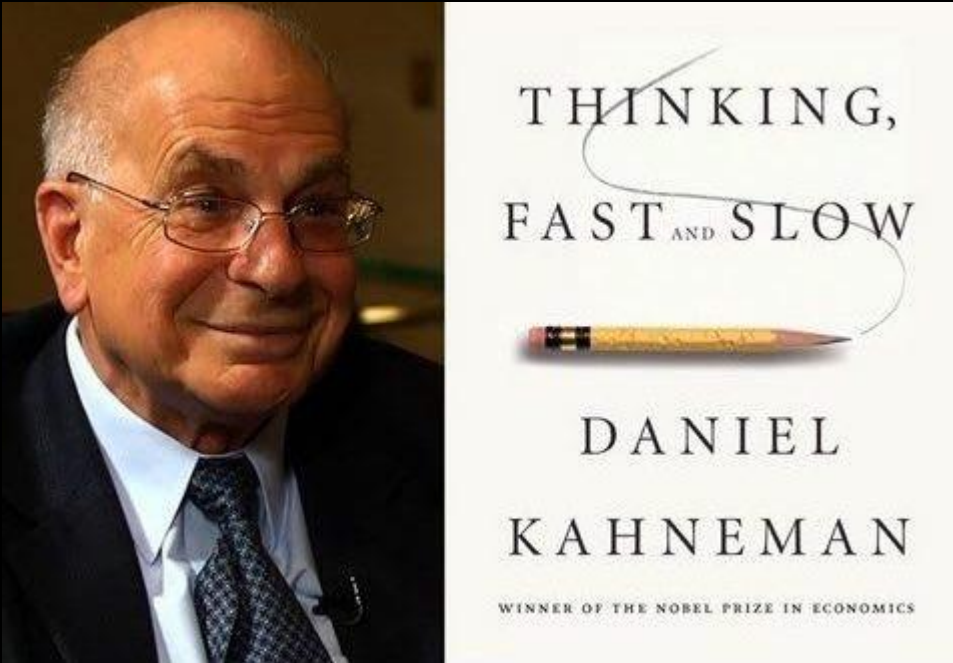


Here we see the effect of risk perception on adaptation: after a flood in Houston in 2001, building codes were improved, and households have invested in flood proofing their homes. This has led to lower damage in 2015 during a flood of similar magnitude



De Ruiter et al., accepted; J. of Flood risk Management





Research by nobel price winner Daniel Kahneman shows how human decision making works. We can distinguish roughly two type of response systems:

System 1: fast, instinctive and emotional

System 2: slower, more deliberative, rational

Human thinking and decision making is **biased**

We think we take rational decisions (Type 2), but mostly follow a heuristic or influenced by cognitive biases (Type 1)

- Humans try avoid losses, often a higher cost than appears from rational cost-benefit analysis
- Human often over-estimate impacts from low probability events

These biases can be seen in surveys. Here some results from a survey on flood risk perceptions in NYC

- High flood risk awareness
 - 87% are aware that they live in a flood-prone area;
 - 13% were not aware
- 62% indicated Hurricane Sandy increased their flood risk perception
- However, before the hurricane event, 33% did not have flood insurance due to low perceptions
- And after the event: 59% of respondents think climate change will increase flood risk; 41% don't think it will

We need to include these behaviors in Flood risk modelling

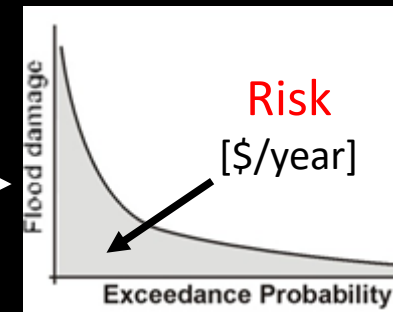
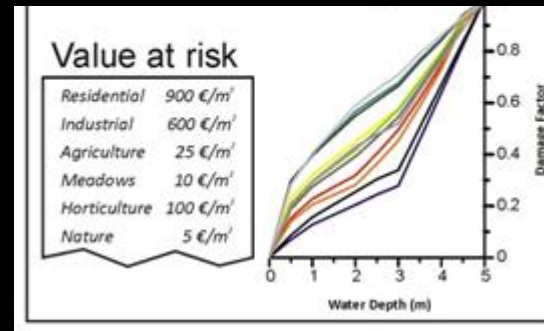
Exposure: assets and people



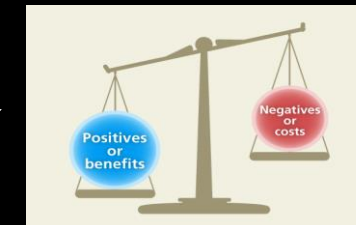
Flood hazard (Extent, depth)



Vulnerability and damage

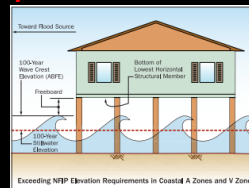


Cost – Benefit analysis



Behavior

Adaptation measures

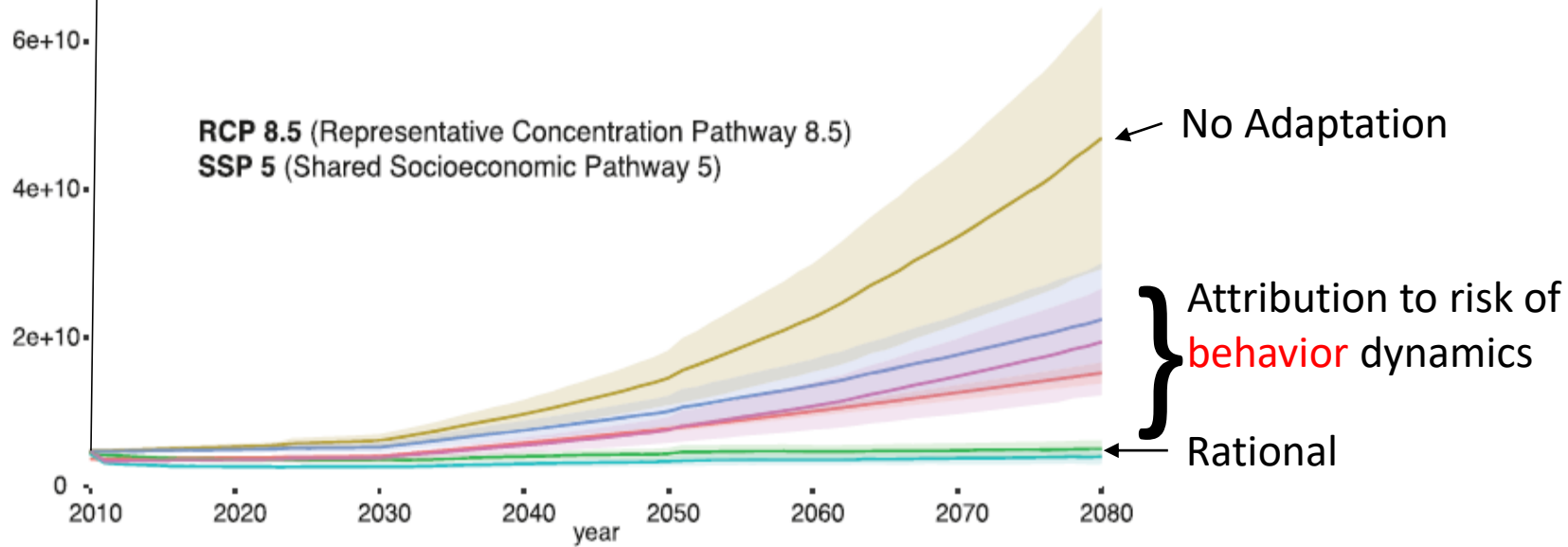


Haer et al., 2019; ERL

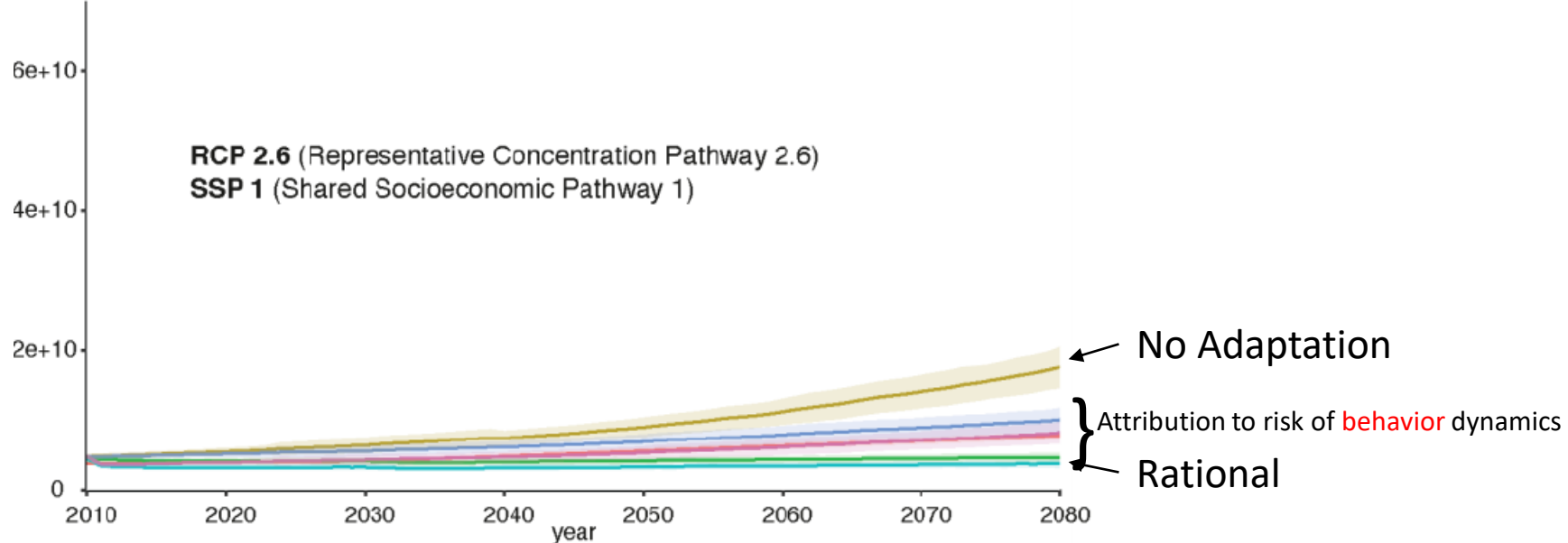
Haer et al (2019) have applied different behavioral theories in a flood risk model to assess (future-) flood risk. Households can be either rational – or bounded rational. Governments either investment in flood protection on a rational (cost-benefit_ basis, or only invest after a extreme flood event

Household	{	Rational	Expected Utility Theory (Von Neumann and Morgenstern, 1947)
		Bounded rational	Prospect theory (Tversky and Kahneman, 1979)
Government	{	Pro active	Rational, before the event)
		Re active	Bounded, after the event)

Flood risk



Flood risk



These graphs show Flood risk in the EU (2010-2080)

It shows that the attribution of different behavioural types on the spread in overall risk is higher than the influence of climate change and urbanization (different in upper and lower graphs)

Haer et al., 2019; ERL

Research Challenges

- Further explore the field of social hydrology (Di Baldessarre et al., 2018) and the paradoxes such as of the adaptation- and levee effects in flood risk research
- Integrate social science theories on behaviour in risk models using e.g. agent based models (Aerts et al., 2018)
- Step up designing surveys to collect empirical data and that fit into physically based risk models (Haer et al. 2020)
- Apply machine learning techniques to assess from novel data bases (e.g. social media; citizen science in general; De Bruin et al., 2019) to derive patterns of how people behave under risk and apply adaptation.

Thanks for your **attention!**

See also: <https://www.youtube.com/watch?v=vt-xS3MOPZ0>

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