

A Budyko-like framework for exploring the controls of long-term flood risk in coupled human-flood systems

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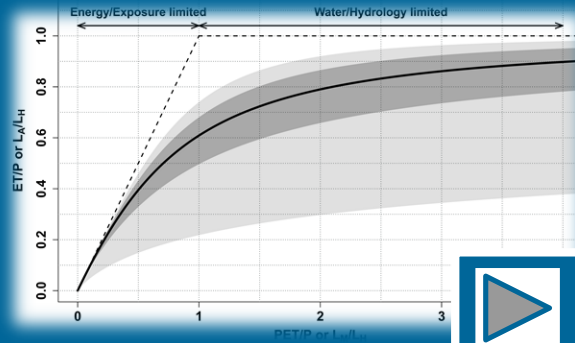
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- We propose a **framework** for exploring the **long-term flood risk** in coupled **human-flood systems** inspired by the Budyko framework.
- Using theoretical stylised systems we illustrate the **influence of different types of social settings** on the position of a system in the flood risk space and how this position may change under the **influence of hydrological, technical and demographic changes**.
- Applying this framework to **empirical cases** enables us to **classify** these **systems** and determine the influence of hydrological and manmade factors on long term flood risk. This is demonstrated for the cases of Cologne and Dresden.
- The framework can help identify **management strategies** that have been proved **useful in other similar systems** to be applied to the system of interest.
- It can help identify “**vicious circles**” or unfortunate developments and help to suggest **counter measures** for flood risk management.

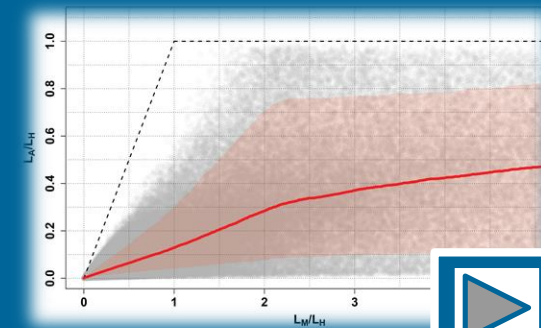
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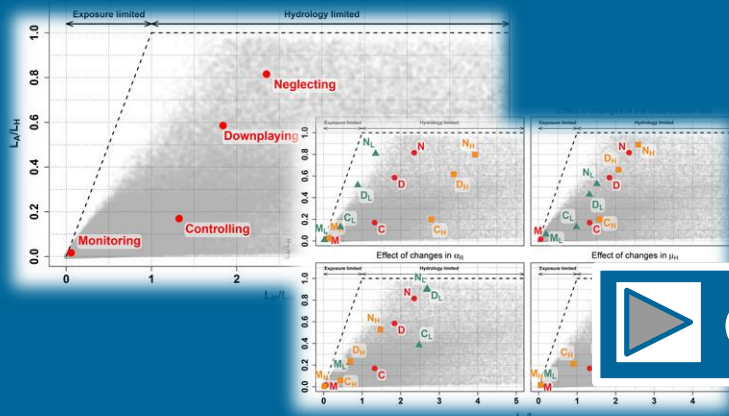
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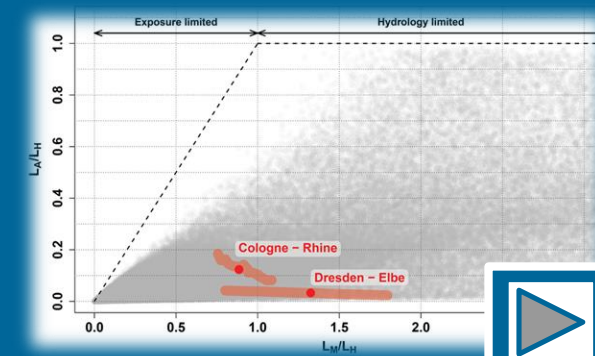
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1. A theoretical flood risk space

Inspired by the Budyko framework which describes the relationship between precipitation P , potential evapotranspiration PET and actual evapotranspiration ET .

The position of a catchment on the Budyko curve depends on the long term coevolution of catchment characteristics and the water balance.

Flood risk also consists of a hydrological component, i.e. discharges and their probabilities, and a human component, i.e. the exposure and vulnerability. In human-flood systems these components coevolve and together they result in a certain flood risk.

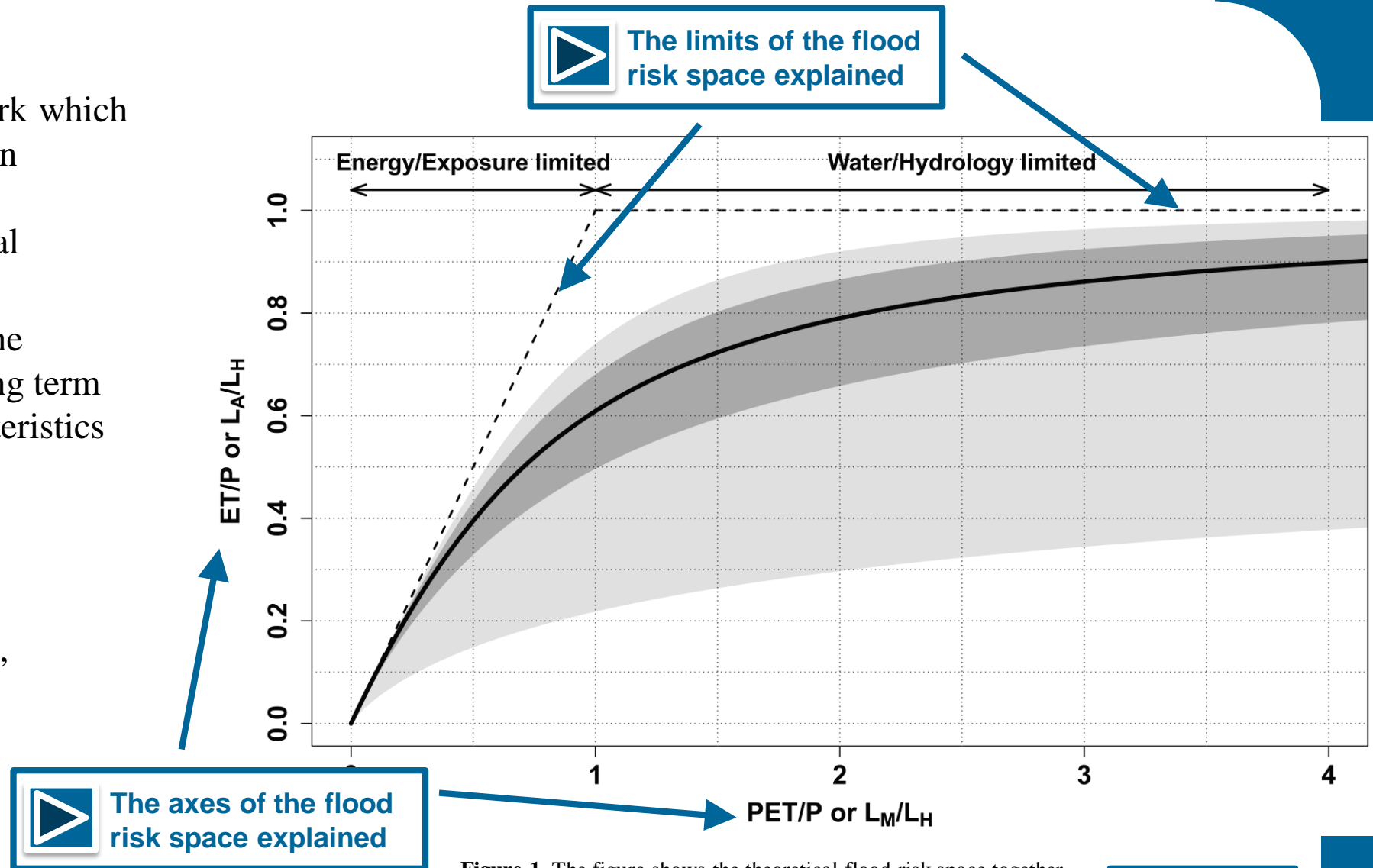
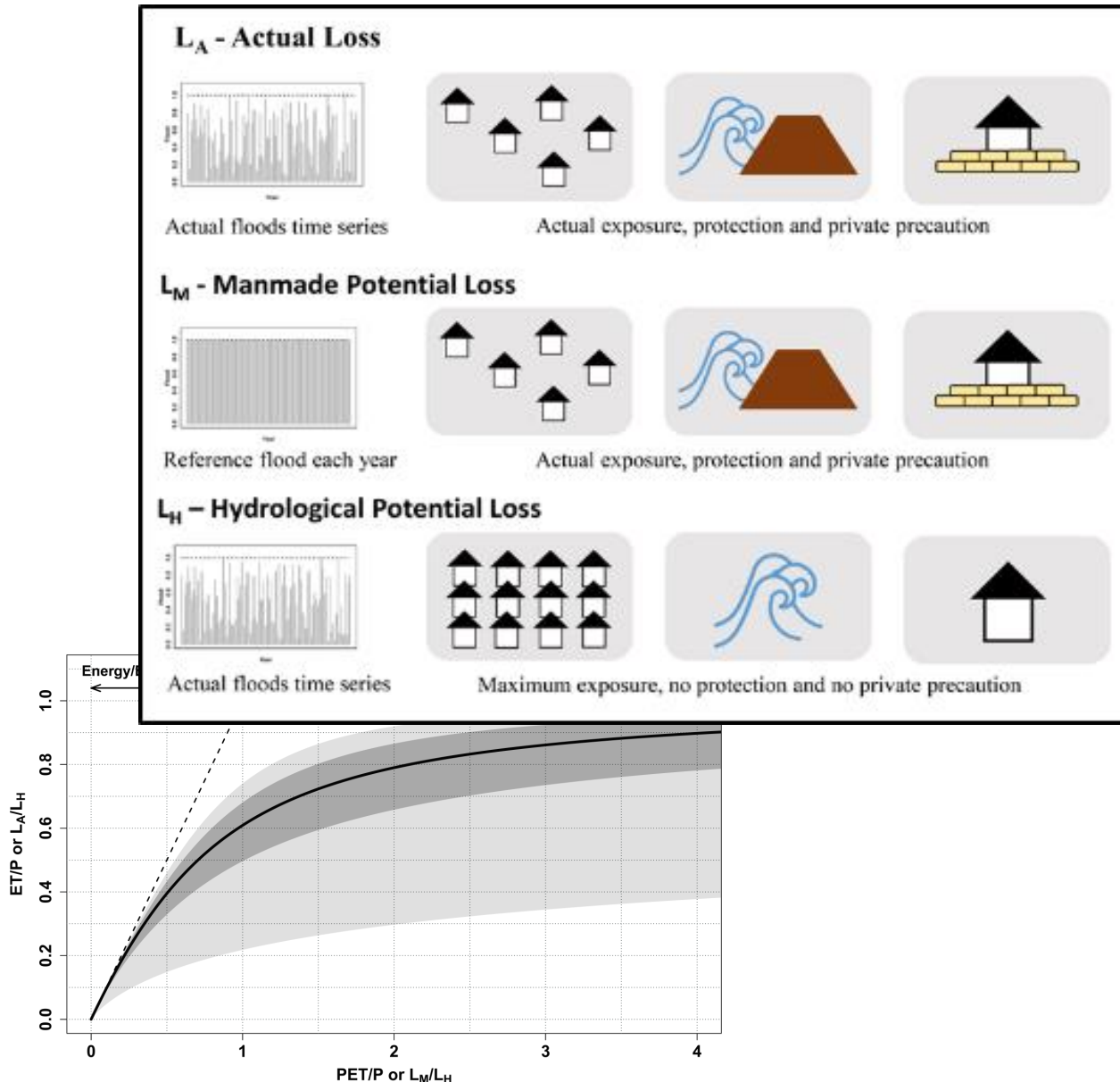


Figure 1. The figure shows the theoretical flood risk space together with the original Budyko space and Budyko curve as developed by Budyko (1974).

The axes of the flood risk space



Y-axis: normalised loss L_A/L_H

X-axis: L_M/L_H

L_A - the average annual loss over a long time period (e.g. a thousand years), considering the actual flood peaks and their probabilities and the actual exposure, structural protection level and level of private precaution.

L_M - the potential loss from a societal perspective. It represents the isolated loss due to exposure and vulnerability, removing the effects of hydrology.

L_H - the available loss from a hydrological perspective and depends on the hydrological characteristics (i.e. the hazard characteristics) of the system.

The limits of the flood risk space

Like the original Budyko space, the flood risk space is limited by the line y is equal to x and the line y is equal to 1.

If the value on the x-axis is between zero and one the system is exposure limited, i.e. the potential loss due to society is smaller than the potential loss due to hydrology. For a system in this area of the flood risk space, the loss is mostly determined by the changes in the exposure and vulnerability and changes in the hydrology (i.e. the hazard) will have less effect on the long term flood risk.

If we move to the right of one on the x-axis, the manmade potential loss becomes higher than the hydrological potential loss. This means that the flood risk is limited by the hydrology (i.e. floods). For a system in this area of the flood risk space, the loss is mostly determined by the changes in the hazard, and changes in the exposure and vulnerability will have less effect on the long term flood risk.

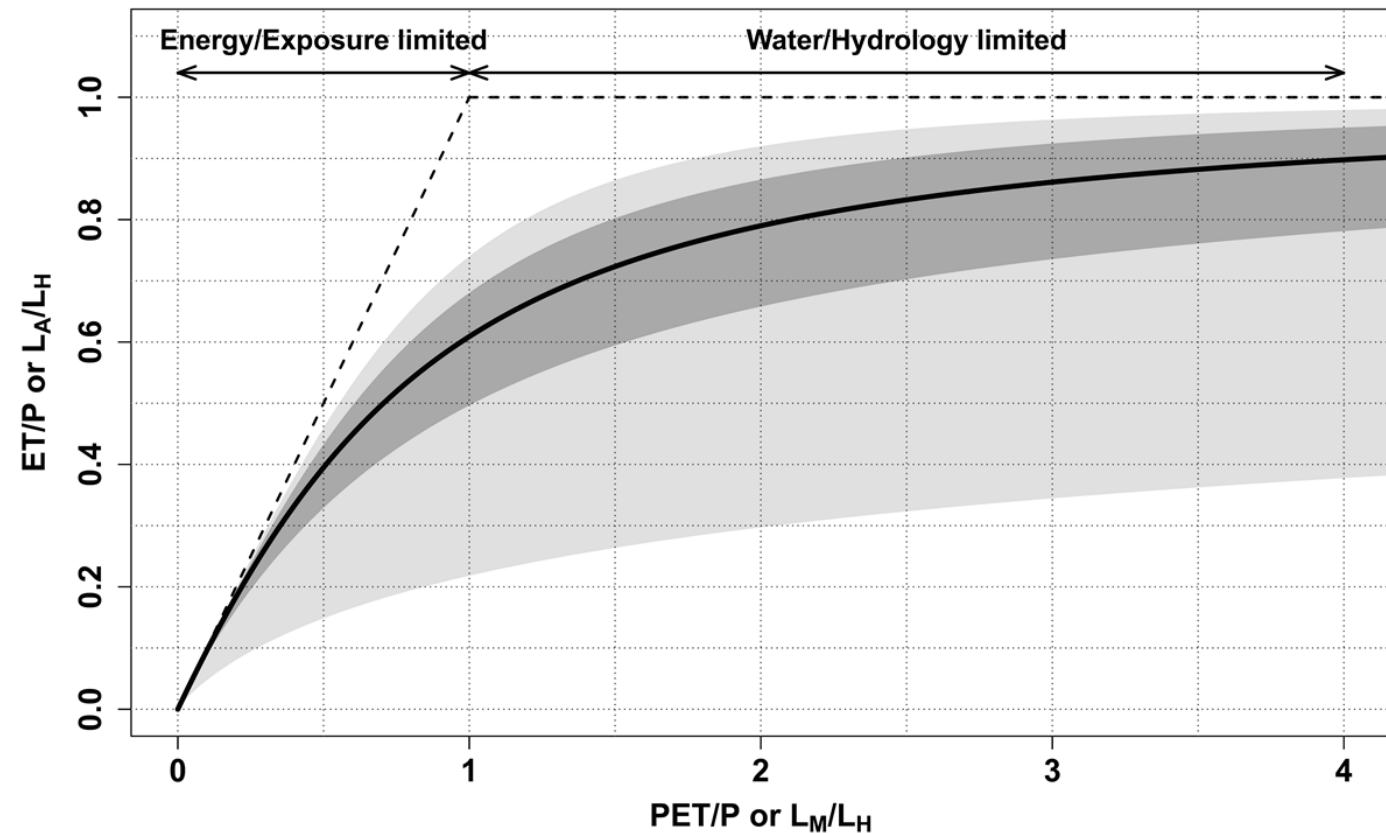


Figure 2. The figure shows the theoretical flood risk space together with the original Budyko space and Budyko curve as developed by Budyko (1974).

2. Populating the flood risk space

Using an adapted version of the model described in Barendrecht et al. (2019) we model the behavior of five hundred thousand theoretical human-flood systems to fill the flood-risk space.



Each system is characterized by a randomly sampled set of parameters.



The model is run one hundred times for a time period of 1000 years, to account for the effects of variability in timing and size of flood events.

The values of the actual loss L_A , hydrological potential loss L_H and manmade potential loss L_M are calculated to determine each system's position in the flood risk space.

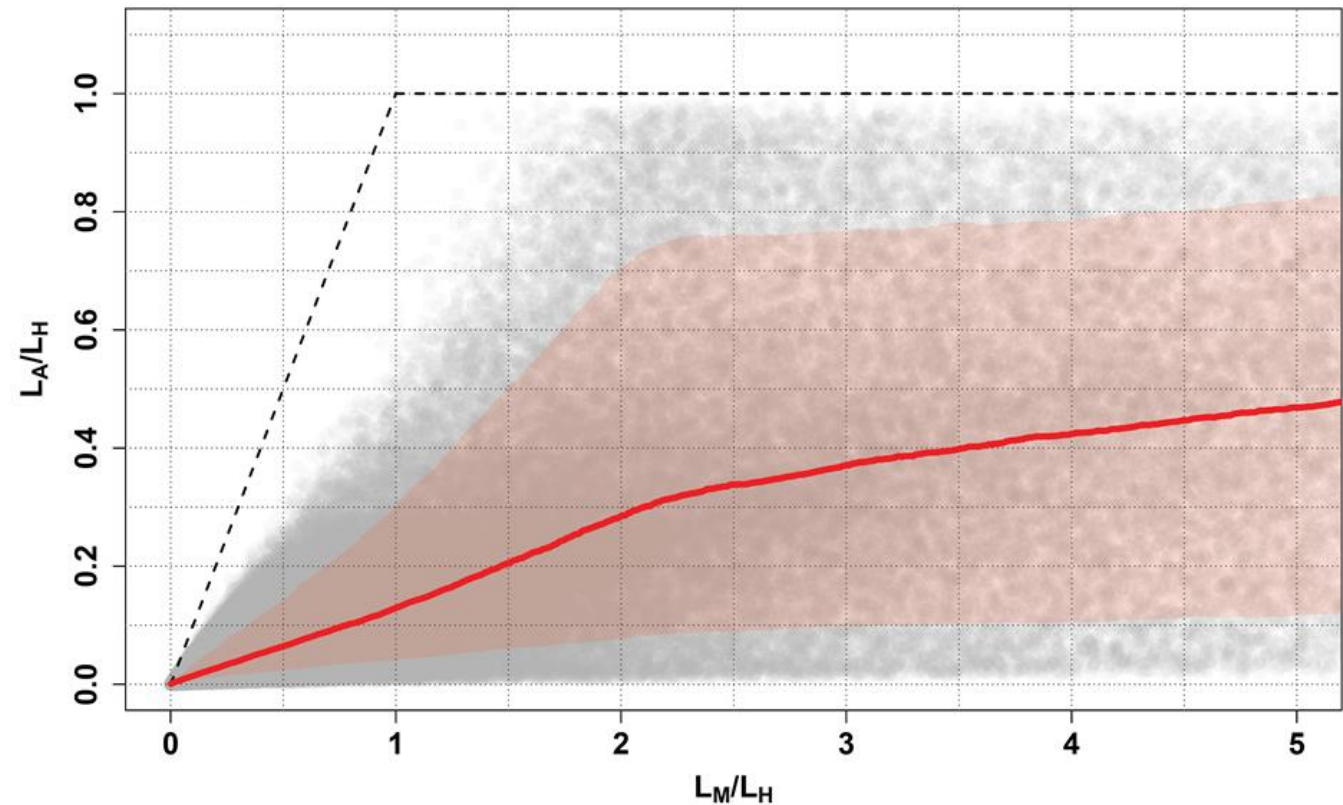


Figure 3. A populated flood risk space. The grey points each represent a theoretical system with a different set of parameter values that was used to run the model. The red line represents the median values and the red shaded area the 90% interval.

The model includes the following variables to describe the feedbacks in a human-flood system: Floods (W), Protection Level (H), Loss (L), Settlement Density (D), Relative Loss (R), Awareness (A) and Preparedness (P). Floods (W) are exogenous and the behavior of the other variables is described with the system of differential equations in equation 1.

$$L_A = \frac{\sum_{f=1}^{100} \frac{\sum_{t=1}^{1000} R_{t,f} D_{t,f}}{1000}}{100} \quad (2a)$$

$$L_H = \frac{\sum_{f=1}^{100} \frac{\sum_{t=1}^{1000} R_H D_{max}}{1000}}{100} \quad (2b)$$

$$R_H = R_{max} - \beta_R \exp\left(-\alpha_R(P_{max} - P_{min}) \frac{W_{t,f}}{W_{max}}\right) \quad (2c)$$

$$L_M = \frac{\sum_{f=1}^{100} \frac{\sum_{t=1}^{1000} R_M D_{t,f}}{1000}}{100} \quad (2d)$$

$$R_M = \begin{cases} R_{max} - \beta_R \exp\left(-\alpha_R(P_{max} - P_{t,f}) \frac{W_{max}}{W_{max}}\right), & W_{max} > H_{t,f} \\ 0, & W_{max} \leq H_{t,f} \end{cases} \quad (2e)$$

$$L = RD \quad [€/€] \quad (1a)$$

$$R = \begin{cases} R_{max} - \beta_R \exp\left(-\alpha_R(P_{max} - P) \frac{W}{W_{max}}\right), & W > H \\ 0, & W \leq H \end{cases} \quad \left[\left(\frac{€}{m^2}\right) / \left(\frac{€}{m^2}\right)\right] \quad (1b)$$

$$\frac{dD}{dt} = U(1 - \alpha_D A) D \left(1 - \frac{D}{D_{max}}\right) \quad [m^2/m^2] \quad (1c)$$

$$\frac{dA}{dt} = \alpha_A L \left(1 - \frac{A}{A_{max}}\right) - \mu_A A \quad [n_h/n_h] \quad (1d)$$

$$\frac{dP}{dt} = \begin{cases} \alpha_P \frac{dA}{dt} \left(1 - \frac{P}{P_{max}}\right) - \mu_P P, & R > 0 \\ -\mu_P P, & R = 0 \end{cases} \quad [n_m/n_m] \quad (1e)$$

$$\frac{dH}{dt} = \begin{cases} \alpha_H (W - H) \text{Bernoulli}(L^{\beta_H}) - \mu_H H, & W > H \\ -\mu_H H, & W \leq H \end{cases} \quad [m/m] \quad (1f)$$

The values of the actual loss L_A , hydrological potential loss L_H and manmade potential loss L_M are calculated according to equation 2.

A description of the model parameters and the ranges used for sampling can be found here.



Parameter	Definition	Unit	Range
U	Urbanisation rate	[1/t]	0.001 – 0.1
W_{\max}	Maximum flood discharge	[m ³ /m ³]	Set to 1
α_D	Risk taking attitude	[1 / (n _h /n _h)]	0 – 20
D_{\max}	Maximum settlement density	[m ² /m ²]	Set to 1
α_A	Anxiousness	[1 / (€ / €)]	0 – 20
A_{\max}	Maximum awareness	[n _h /n _h]	Set to 1
μ_A	Forgetfulness	[1 / t]	0 – 1
μ_P	Decay rate of precautionary measures	[1 / t]	0 – 1
P_{\max}	Maximum preparedness	[n _m /n _m]	Set to 1
α_P	Activeness	[(n _m /n _m)t / (n _h /n _h)]	0 – 20
R_{\max}	Maximum relative loss	[(€ / m ²) / (€ / m ²)]	Set to 1
β_R	Discharge to loss relationship	[(€ / m ²) / (€ / m ²)]	Set to 1
α_R	Effectiveness of preparedness	[1 / (n _m /n _m)]	0 – 1
α_H	Increase rate structural protection	[1/t]	0 – 1
β_H	Protectiveness	[-]	0 – 1
μ_H	Decay rate of structural protection	[1 / t]	0 – 0.1
MAF	Mean annual flood	[m ³ /s]	0 – 100000
L-Skewness	L-Skewness	[-]	0.14 – 0.4
L-CV	L-Coefficient of variation	[-]	0.192 + 1.139(L-Skewness-0.17) + N(0, 0.03)



3. Stylised systems in the flood risk space

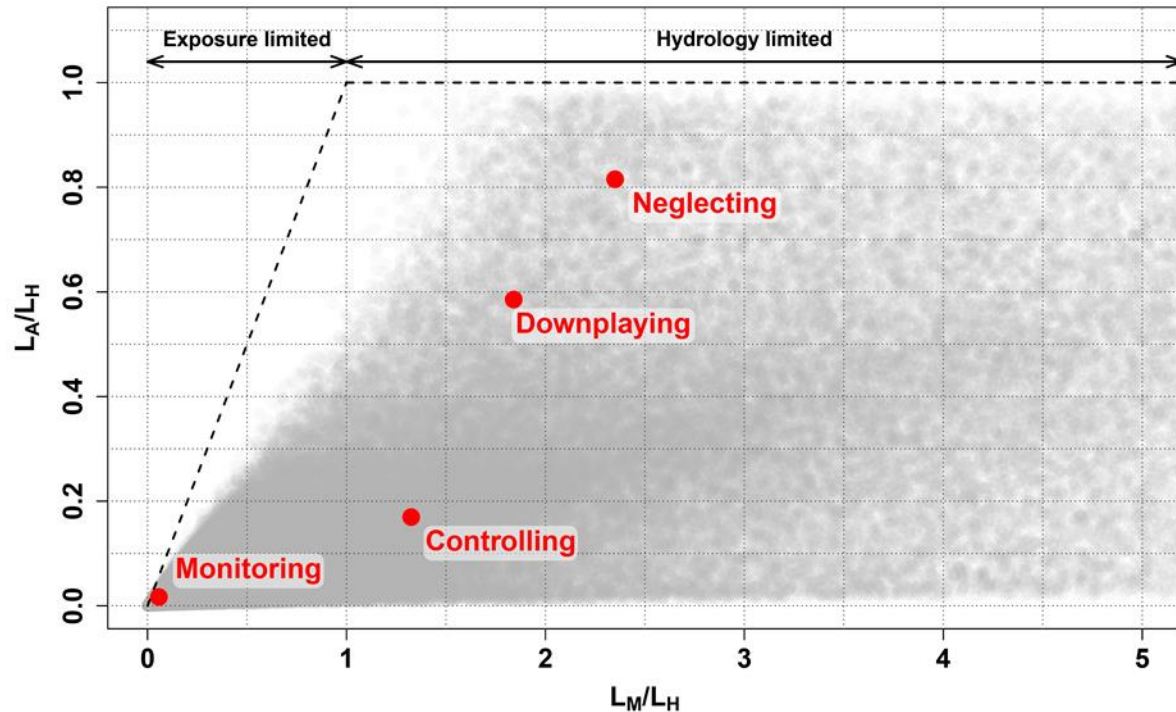


Figure 4. The four synthetic systems in the flood risk space (red points). The black points each represent a theoretical system generated with a random set of parameter values as explained in section 2.

The effects of other system characteristics (i.e. parameter values) on the position of the four stylised systems are investigated by varying their values.

[▶ The effects of other characteristics](#)

Following the example of Ridolfi et al. (2019) we investigate the position of four stylised societies.

[▶ Stylised systems defined](#)

Risk neglecting systems have a high normalised long term flood loss, since this society does not do much to reduce flood risk. It is hydrology limited, since the risk is more influenced by changes in hydrology, because not is done to control exposure and vulnerability, .

The **risk downplaying** system is a little bit better off, since it does take some measures to reduce risk. However, this society has limited awareness to floods and therefore, even though society may take some measures, it has a relatively high normalised long term flood loss.

Both the **risk monitoring** and the **risk controlling** systems have a lower normalized long term flood loss than the other two systems. The risk monitoring system is exposure limited, while the risk controlling system is hydrology limited. In the case of the risk monitoring system, the flood loss is minimised by reducing the exposure and vulnerability. The risk controlling system minimises risk by attempting to control the hazard and reduce the occurrence of floods.

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Parameter	Parameter definition	Risk neglecting	Risk controlling	Risk downplaying	Risk monitoring
α_D	Risk taking attitude	Low - 1	Medium - 5	Medium - 5	High - 20
α_A	Anxiousness	Medium - 7	Medium - 7	Low - 3	High - 15
μ_A	Forgetfulness	Medium - 0.6	Medium - 0.4	High - 0.8	Low - 0.2
μ_P	Decay rate of precautionary measures	High - 0.8	Medium - 0.4	High - 0.8	Low - 0.2
α_P	Activeness	Low - 1	Medium - 5	Medium - 5	High - 20
α_H	Increase rate structural protection	Low - 0.2	High - 0.8	Medium - 0.4	Low - 0.2
β_H	Protectiveness (low values mean high protectiveness)	Low - 0.8	High - 0.2	Low - 0.8	Medium - 0.5

The risk neglecting society does not take any measures to reduce the risk, because its assumption is that managing the risk is not possible or too costly.

The risk controlling society depends on structural measures to reduce risk.

The risk downplaying society underestimates the flood risk. This society may take measures to reduce the risk, but it tends to forget about flood risk fast and does not put much effort in maintaining its awareness and risk reduction measures.

The risk monitoring society believes that it cannot control its environment, but can control society. Its risk management strategy is focused on reducing settlement in the floodplain and being prepared for events that will happen by taking precautionary measures.

For a detailed explanation and the theoretical foundation of these four types of societies, we refer to Ridolfi et al. (2019).

Ridolfi, E., Albrecht, F., & Di Baldassarre, G. (2020). Exploring the role of risk perception in influencing flood losses over time. Hydrological Sciences Journal, 65(1), 12-20.



The influence of the following system characteristics on a system's place in the flood risk space are investigated:

- Hydrological (skewness and CV of the flood frequency curve, the decline of structural protection μ_H)
- Technical (the effectiveness of preparedness α_R)
- Demographic (the urbanization rate U)

For each characteristic we run the model for the four systems with a low (triangle) and a high (square) value of the corresponding parameter.

The effect of varying these parameters is shown in Figure 5.

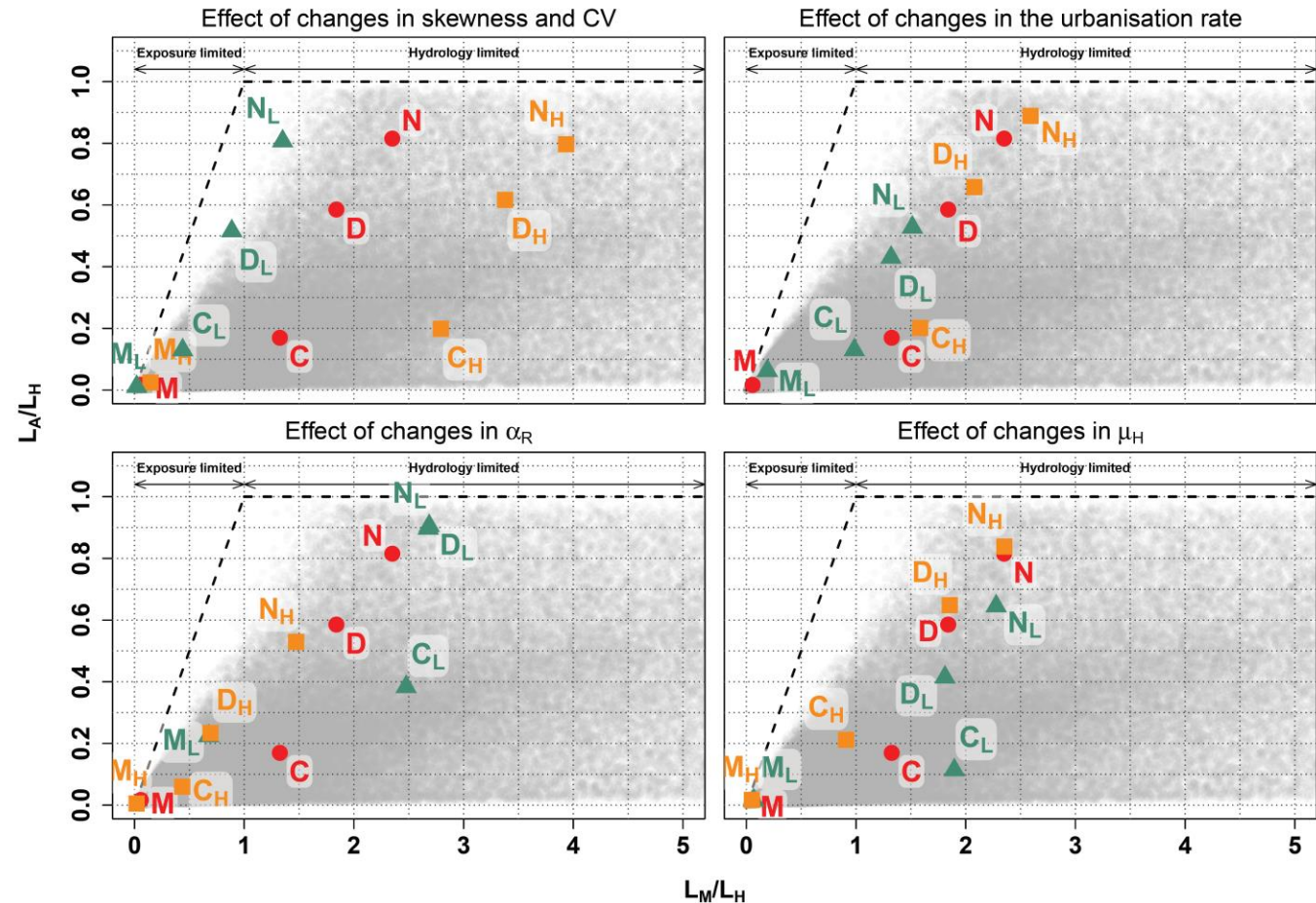


Figure 5. The effects of changes in the hydrological (skewness and CV of the flood frequency curve, the decline of structural protection μ_H), technical (the effectiveness of preparedness α_R) and demographic (urbanization rate, U) parameters. The red dots represent the four synthetic systems: risk neglecting (N), risk downplaying (D), risk controlling (C) and risk monitoring (M). The blue triangles and the yellow squares represent the same systems but with a lower and higher value of the investigated parameter, respectively.

4. Empirical cases in the flood risk space

The framework is applied to the case studies of Dresden and the river Elbe (see also Barendrecht et al. 2019) and Cologne and the river Rhine both in Germany.

According to our framework, Cologne is an exposure limited system, while Dresden is a hydrology limited system. In Cologne variations in the long term flood loss will be mostly due to variations in the exposure and vulnerability, while in Dresden variations will be mostly due to variations in flood magnitude.

Therefore, even if Dresden would adapt more in order to reduce flood risk, in the long-term the average flood loss will still be controlled by the severity of the events and more or less measures will not have a big influence on the long-term flood risk.

In Cologne, an increased (or decreased) adaptation to flood risk will have a larger influence on the long-term flood risk. This difference is also reflected in the behaviour of the two systems.

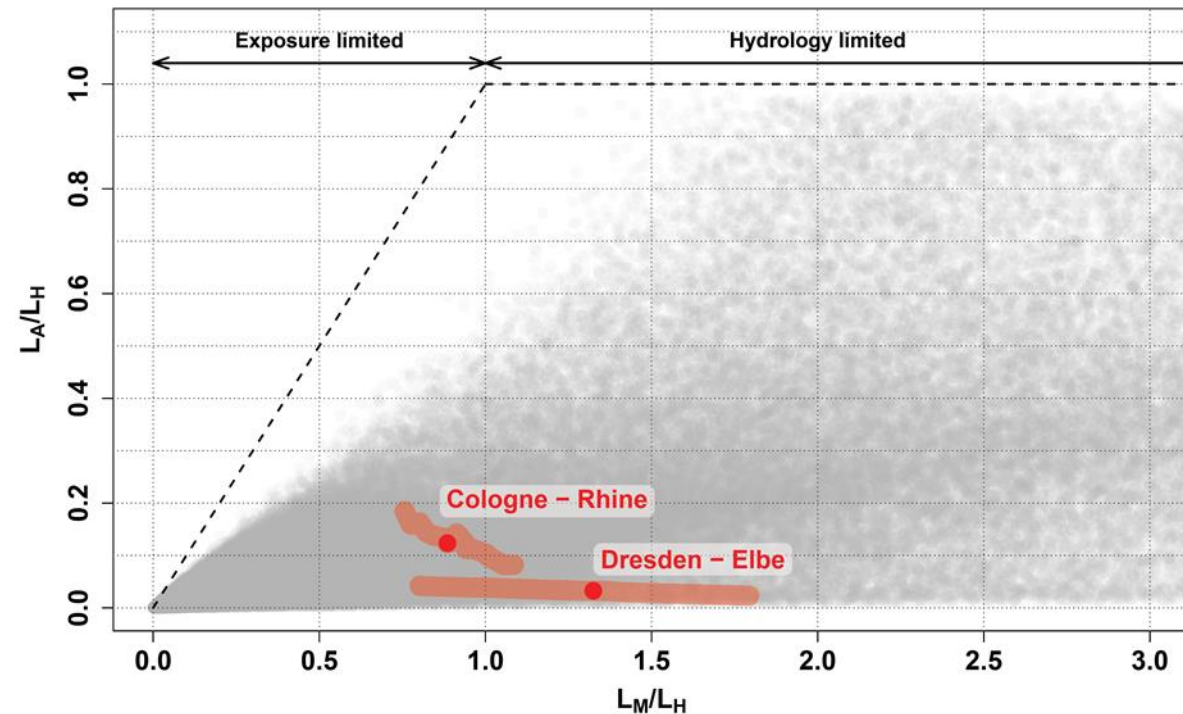


Figure 6. Empirical cases on the flood risk curve. Red dots represent the two empirical cases: Dresden and the Elbe and Cologne and the Rhine. The red lines around the dots represent the uncertainty due to the estimation of the parameters related to the structural protection (α_H , β_H and μ_H). The grey dots represent all the modelled systems as explained in section 2.



System behaviour
Dresden vs Cologne



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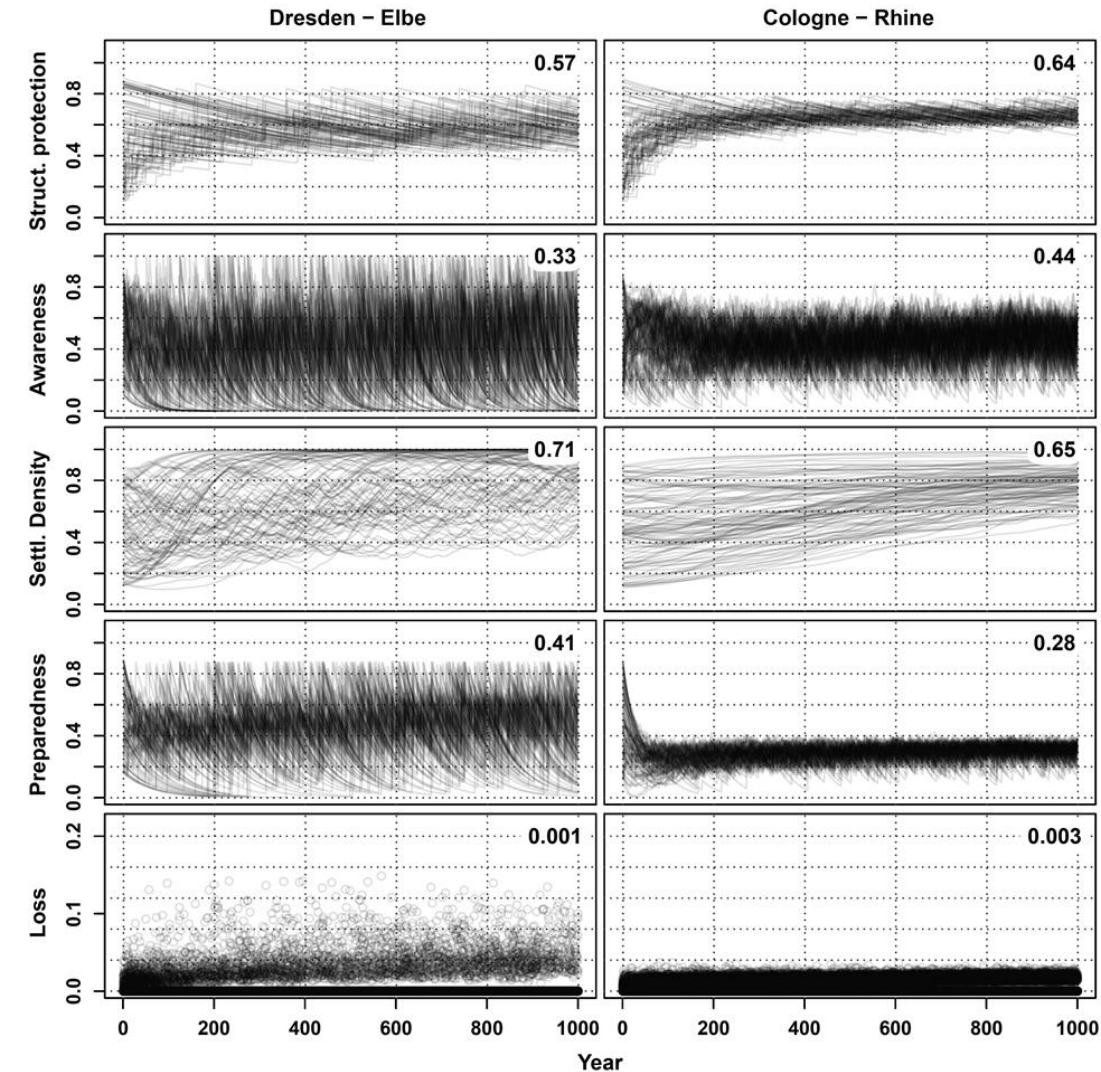


Figure 7. Time series for each of the hundred model runs for the two empirical cases (Dresden and Cologne). The averages over the time period are given in the top right corner of each panel.

The difference between the Dresden and Cologne systems seems to be mostly caused by the hydrological parameters rather than the social parameters. The annual peak discharges of the Elbe at Dresden have a CV of 0.49 and a skewness coefficient of 1.19 and the annual peak discharges of the Rhine at Cologne have a CV of 0.29 and a skewness coefficient of 0.35 (see also the L-moments reported in table 3). The flood frequency distribution is more skewed in the case of the Elbe in Dresden than in the case of the Rhine in Cologne.

Therefore, Dresden experiences more shocks (i.e. unexpectedly large floods) to the system than Cologne. This is also reflected in the time series plotted in Figure 7 and the average long term values of the variables given in the top right corners of the panels in Figure 7.

Because of the more regular and similar flooding, the awareness in Cologne is higher on average and does not get as close to zero as it does in Dresden at some points in time. The preparedness in Cologne neither gets as close to zero in Cologne as it does in Dresden. However, the increases in awareness and preparedness are on occasion much higher in Dresden than in Cologne and they also decline much more, sometimes getting close to zero.