Towards understanding nitrogen legacies in European catchments

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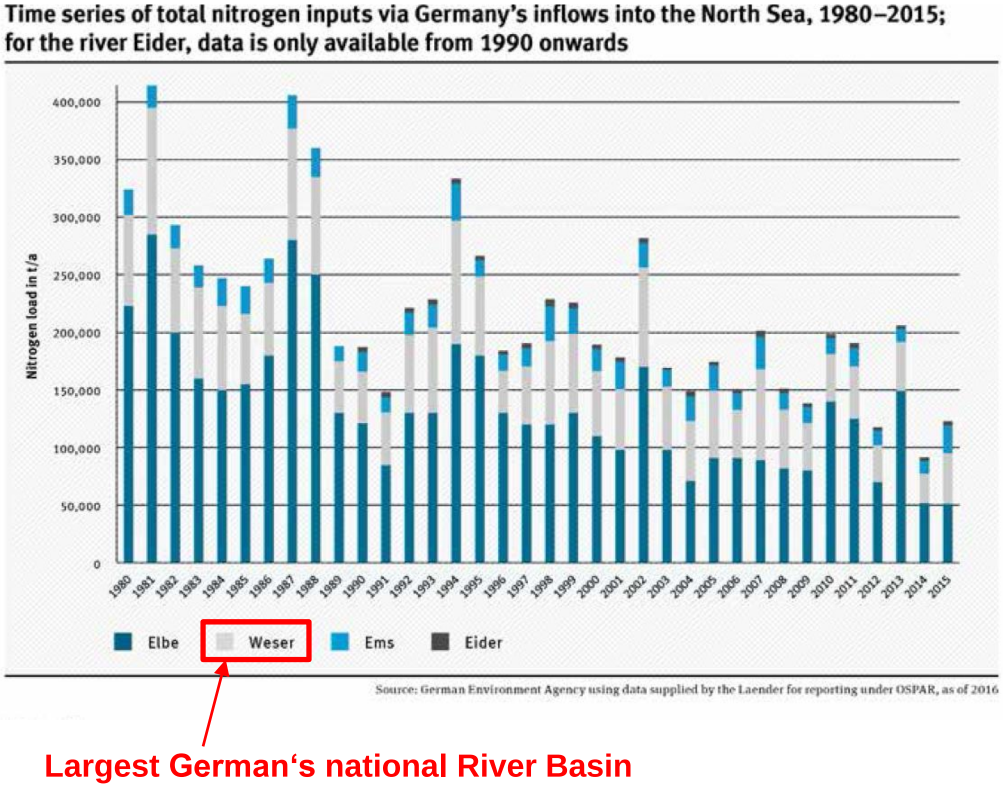
Nitrogen (N) compounds present in the Weser river are contributing to the eutrophication of the North sea

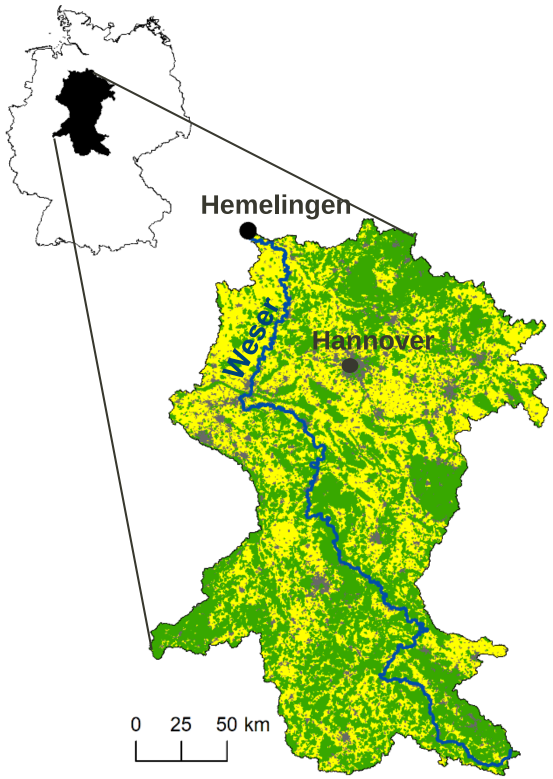

Green algae on tidal flats
Source: Dr. Wera Leujak


Foam algae on a North Sea beach
Source: Ulrich Claussen

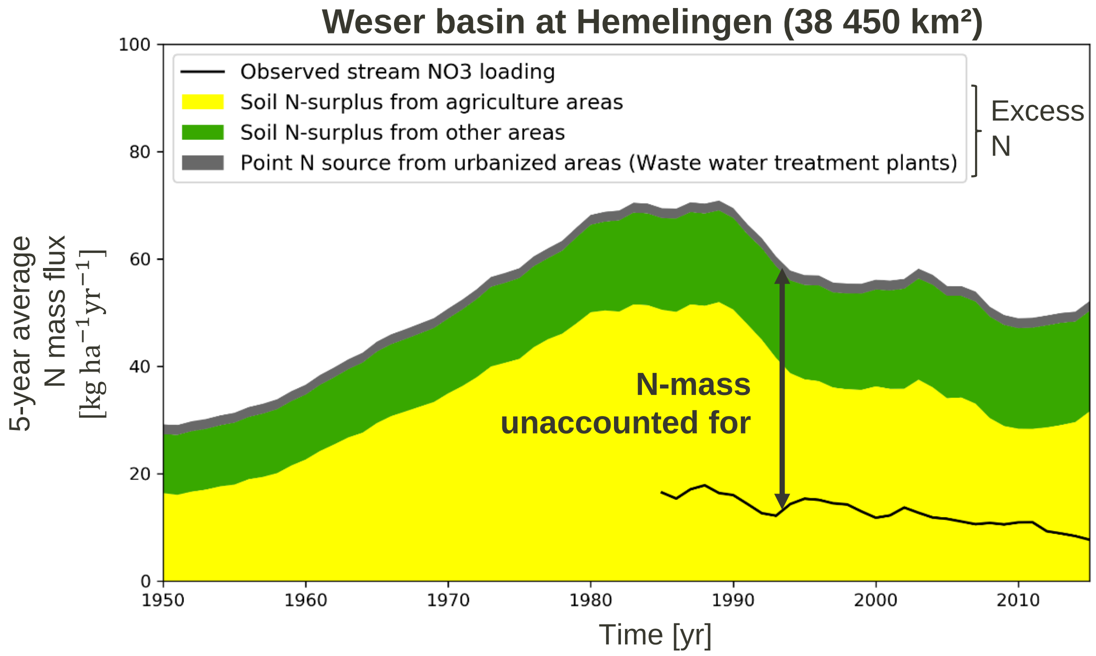
[German Environment Agency, 2017]



Soil N-surplus, mostly over agricultural areas, is responsible for stream nitrate (NO3) pollution in the Weser River basin...



45% of agricultural land

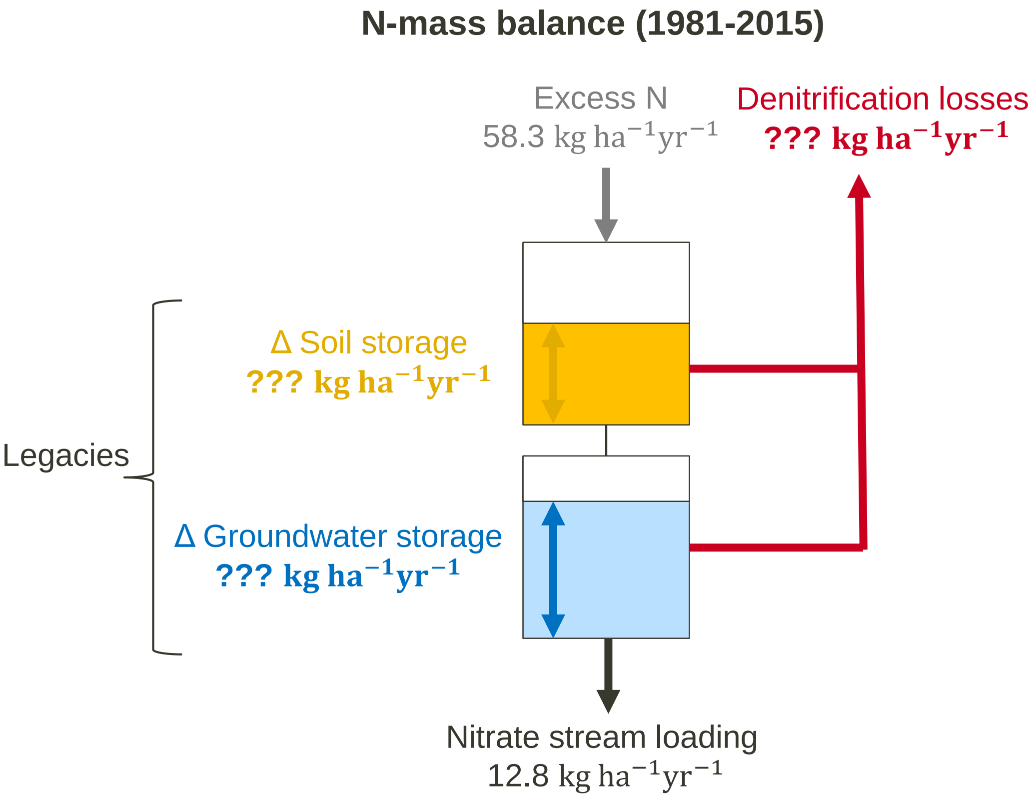


... but a large fraction of the excess N mass is unaccounted for (not found in the stream).

Are soil and groundwater N legacies building up in the Weser basin?

- It is critical to understand the build-up of nitrogen legacy stores over time, as they can have a large impact on future stream N loading, and thus compromise the achievement of reduction goals for N levels.

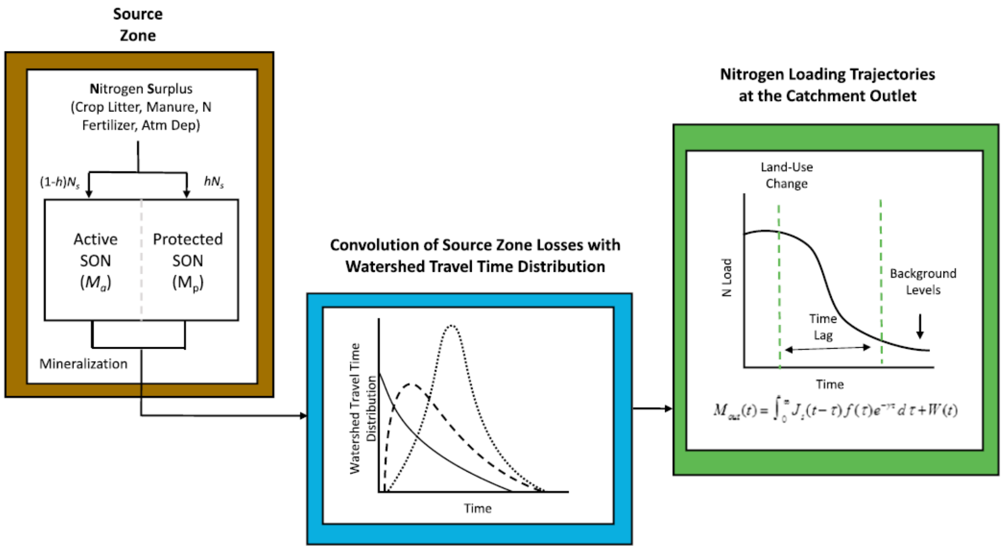
- We apply a mechanistic nitrate model to assess the fate of excess N (lost through denitrification or stored in the system – soil or groundwater).



We use a parsimonious modelling approach: ELEMENT model

- allows for investigation of long term N trajectories at catchment scale and annual time scale
- accounts for legacies in soil and groundwater
- three N pools in the soil (organic active, organic protected and inorganic NO3)
- one N pool in the groundwater (inorganic NO3)

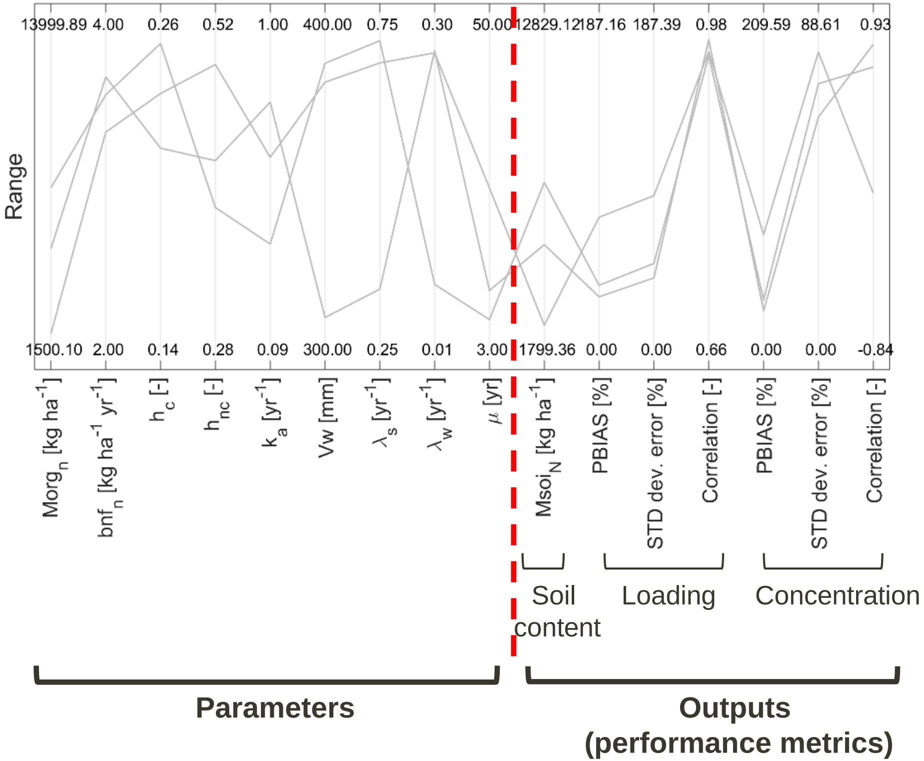
Parameter	Description
$M_{org,n}\ [kg\ ha^{-1}]$	Soil organic N stock under pristine conditions
$bnf_n\ [kg\ ha^{-1}]$	N-surplus under pristine conditions (i.e. biological fixation)
$h_c\ [-]$	Soil organic N protection coefficient for cropland
$h_{nc}\ [-]$	Soil organic N protection coefficient for non-cultivated land use
$k_a\ [yr^{-1}]$	Rate of mineralisation for soil active pool
$V_w\ [mm]$	Mean annual soil water content
$\lambda_s\ [yr^{-1}]$	Rate of denitrification in soil
$\lambda_w\ [yr^{-1}]$	Rate of denitrification in groundwater
$\mu\ [yr]$	Mean travel time in groundwater



[Van Meter et al., 2017, Global Biogeochem Cycles]

We estimate the 9 model parameters using soft rules to account for uncertainties in the model inputs and in the output measurements

- We reduce the number of behavioural parameter sets by sequentially applying soft rules, using the SAFE toolbox for sensitivity analysis (Pianosi et al., 2015).
- We constrain the simulated **current soil N content**, **stream N loading** and **stream N concentration**.
- For loading and concentration, we select simulations based on the different components of the **Kling Kupta Efficiency** (KGE) (percent bias - *PBIAS*, standard deviation error - *STD dev. Error,* and pearson correlation coefficient - *Correlation*).



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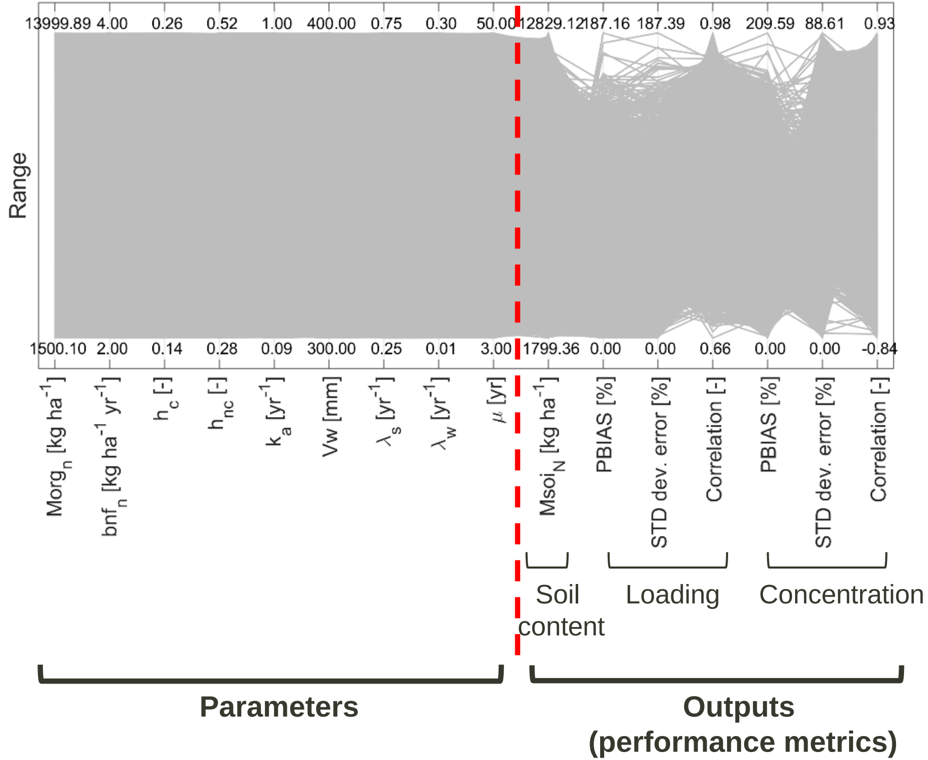
Initial parameter sample	100 000 sets



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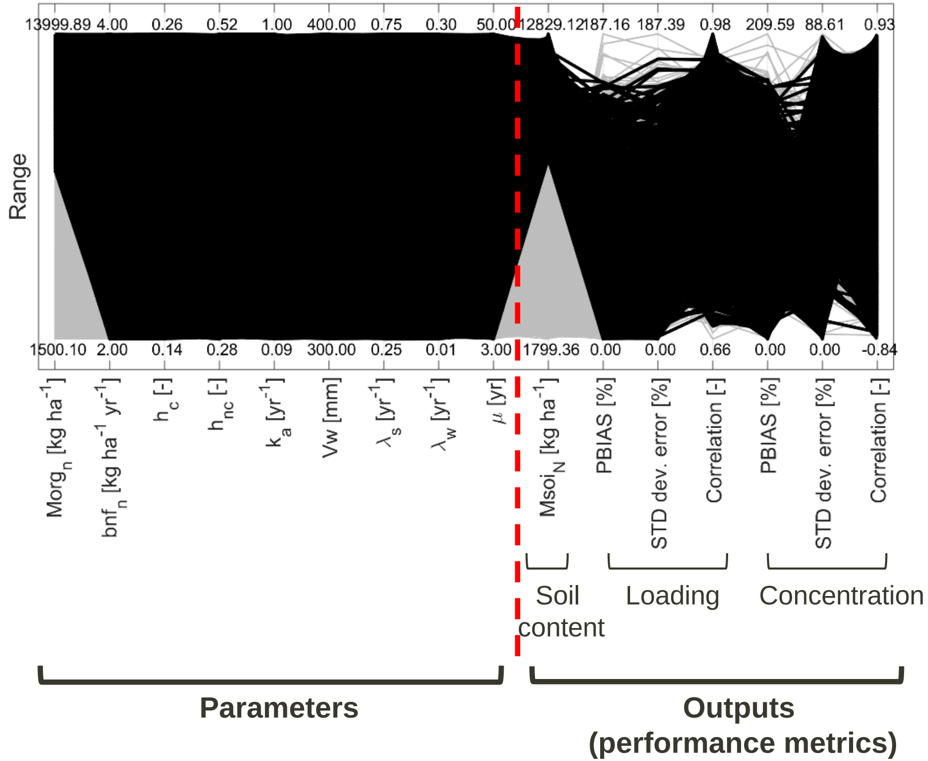
Rule 1: Current soil N content in [8300, 14 000]	**40 021 behavioural sets**



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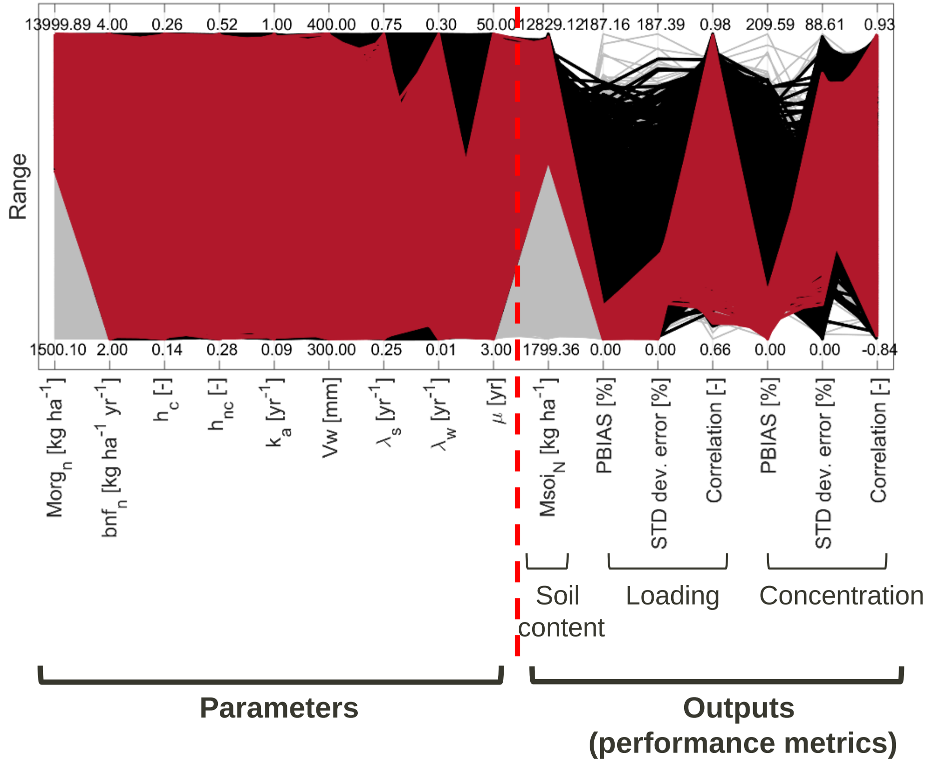
Rule 2: Loading PBIAS ≤ 20%	**6387 behavioural sets**



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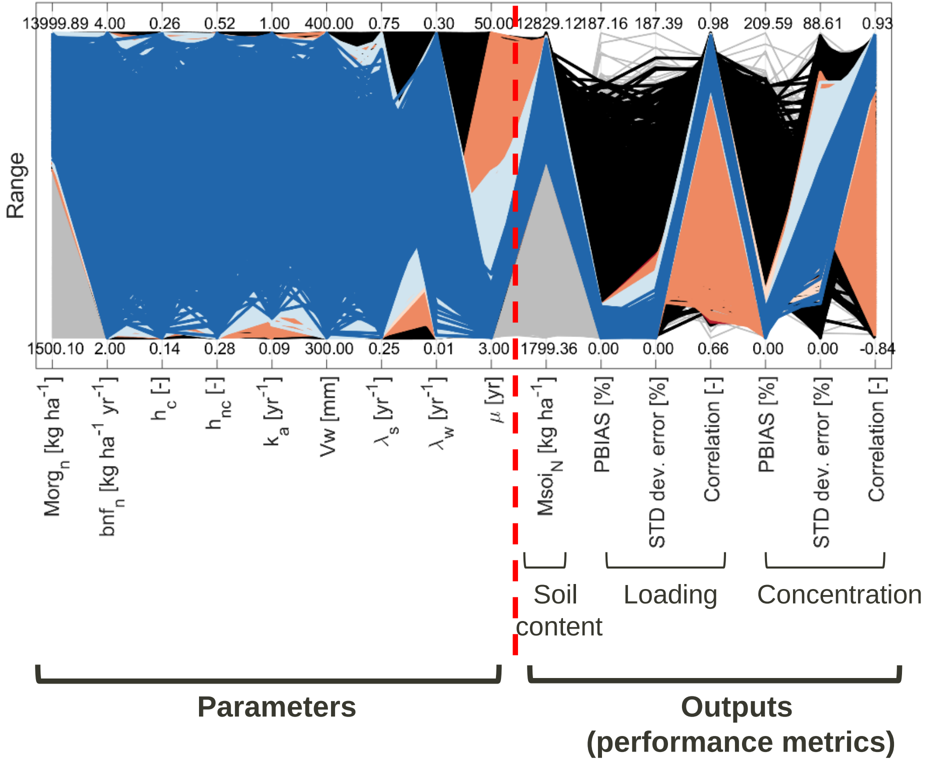
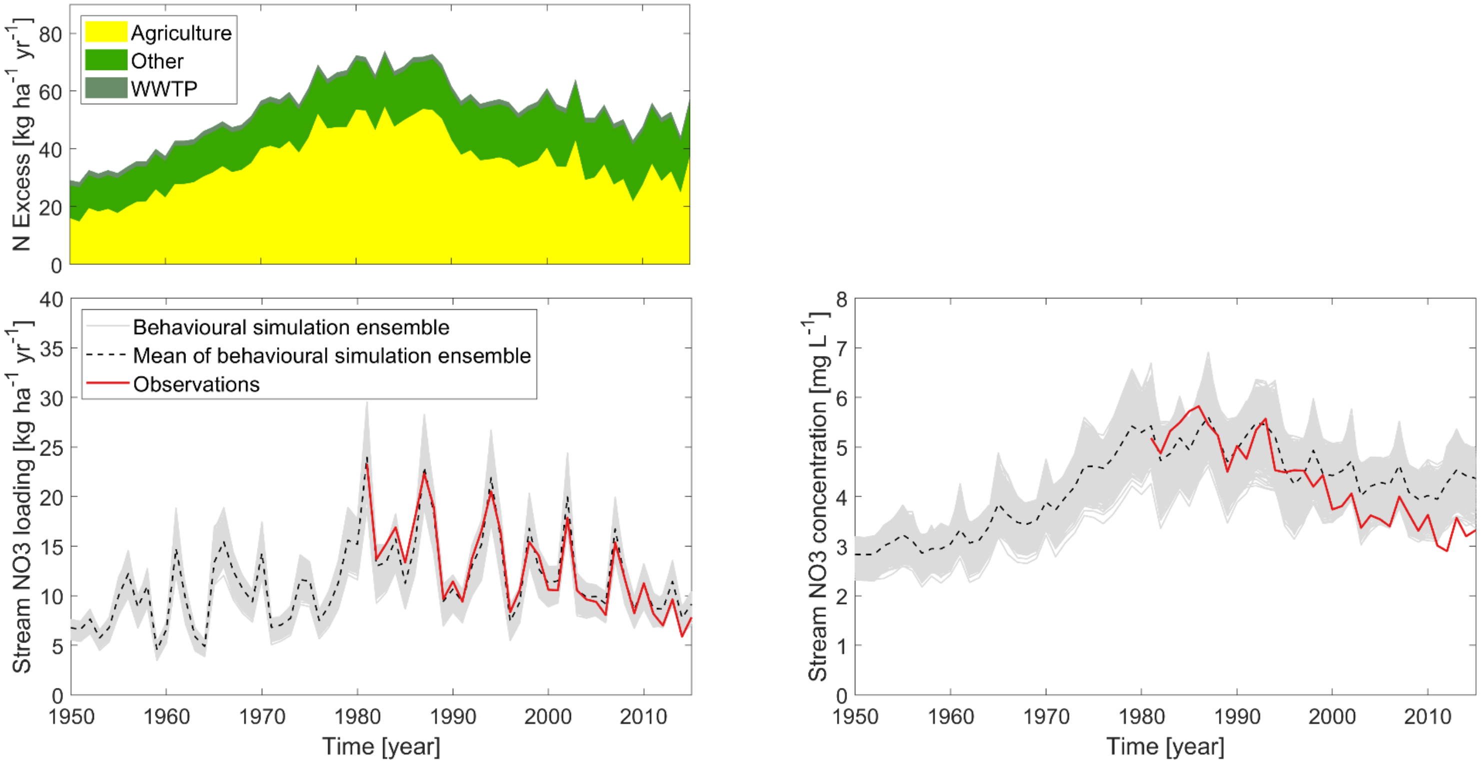
Initial parameter sample	100 000 sets
Rule 1: Current soil N content in [8300, 14 000]	40 021 behavioural sets
Rule 2: Loading PBIAS ≤ 20%	6387 behavioural sets
Rule 3: Loading STD dev. error ≤ 50%	6381 behavioural sets
Rule 4: Loading Correlation ≥ 0.6	3327 behavioural sets
Rule 5: Concentration PBIAS ≤ 20 %	2806 behavioural sets
Rule 6: Concentration STD dev. error ≤ 50 %	643 behavioural sets
Rule 7: Concentration Correlation ≥ 0.6	$\boxed{\text{643 behavioural sets}}$

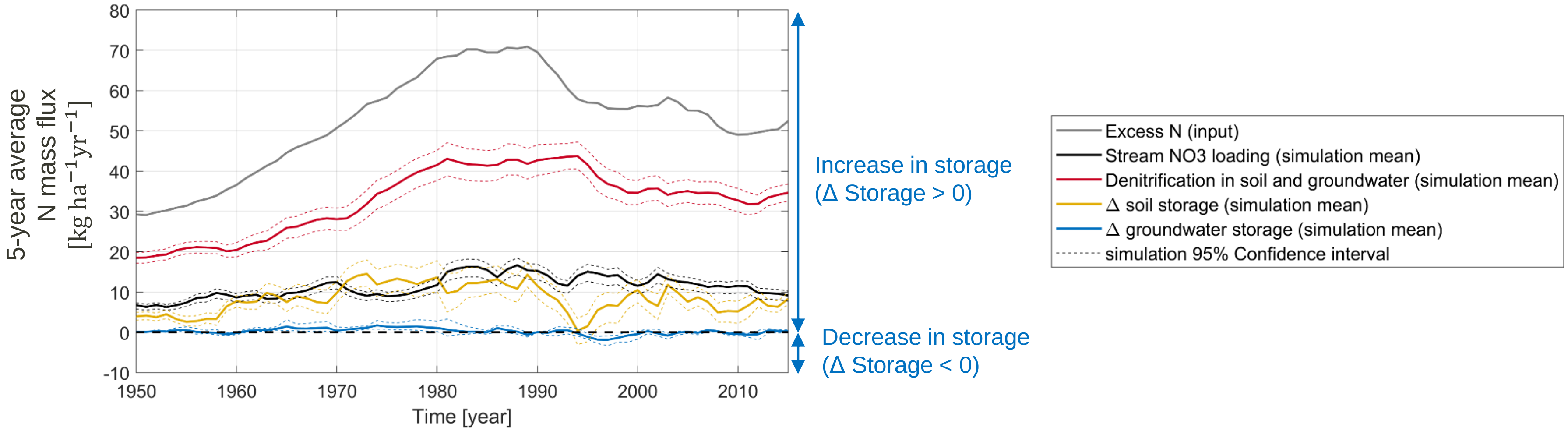
Selected sets



The behavioural simulation ensemble captures the observed stream NO3 loading and concentration



The behavioural simulations allows to estimate the different components of the N mass balance.



- The excess N mass largely denitrifies.
- The soil N storage is increasing, while the groundwater storage only shows limited variations.

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Conclusions and outlook

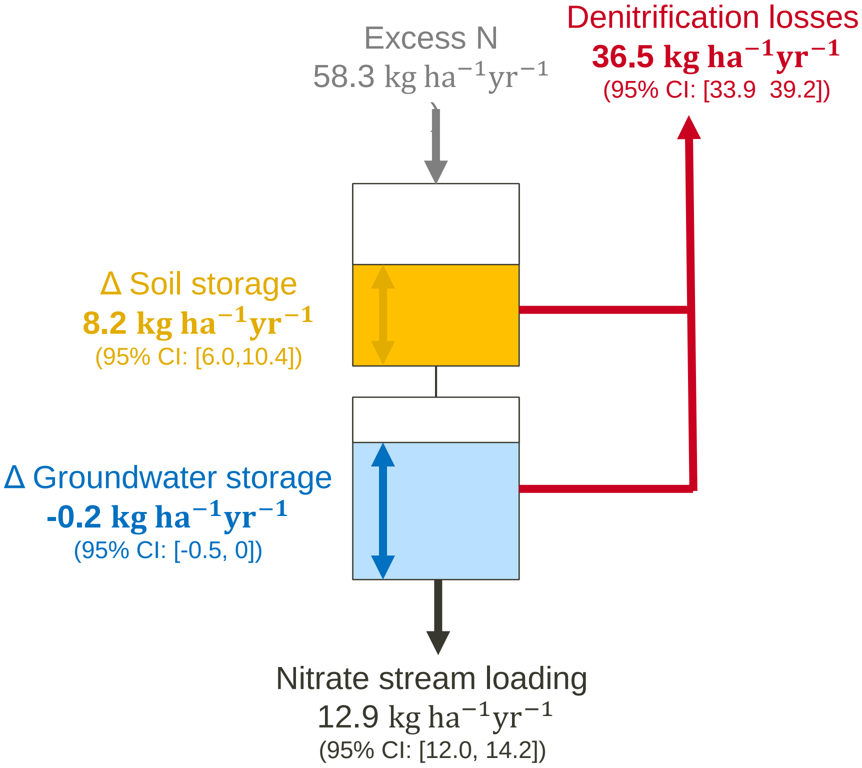
- ELEMENT is able to reproduce the observed stream NO3 loading and concentration in the Weser basin at Hemelingen.

- We separate the excess N into the different components (denitrification, stream loading and storage change), despite the uncertainty that remains after parameter estimation (due to equifinality).

- Simulations show that large part of N is denitrified (around 63% of excess N), but a substantial part is also stored in the soil.

- Future works will focus on different subbasins of the Weser to understand how the fate of the excess N varies spatially.

N mass balance for the Weser basin at Hemelingen (1981-2015)



Source of the data used for parameter estimation and references

- **Source of the data used for the parameter estimation**

Stream NO3 concentration observations for the Weser at Hemelingen was obtained from the Flussgebietsgemeinschaft (FGG) Weser data bank (https://datenbank.fgg-weser.de/weserdatenbank/#/).

Current soil N content observations for the Weser at Hemelingen was estimated from the LUCAS dataset (Ballabio et al., 2016, 2019) available from the ESDAC (European Soil Data Centre, esdac.jrc.ec.europa.eu, European Commission, Joint Research Centre).

- **References**

Ballabio C., Panagos P., Montanarella L. (2016). Mapping topsoil physical properties at European scale using the LUCAS database. Geoderma. 261. 110–123.

Ballabio, C., Lugato, E., Fernández-Ugalde, O., Orgiazzi, A., Jones, A., Borrelli, P., Montanarella, L. and Panagos, P. (2019). Mapping LUCAS topsoil chemical properties at European scale using Gaussian process regression. *Geoderma*, 355. 113912.

German Environment Agency (2017). Waters in Germany: Status and assessment. Dessau-Roßlau.

Pianosi, F., Sarrazin, F., Wagener, T. (2015). A Matlab toolbox for Global Sensitivity Analysis, Environmental Modelling & Software. 70. 80–85 (www.safetoolbox.info).

Van Meter, K. J., Basu, N. B., & Van Cappellen, P. (2017). Two centuries of nitrogen dynamics: Legacy sources and sinks in the Mississippi and Susquehanna River Basins. Global Biogeochemical Cycles. 31(1). 2–23.