Ministeriet for Fødevarer, Landbrug og Fiskeri

STØTTET AF

Promilleafgiftsfonden for landbrug

T-REX
WP3

Spatially differentiated N-retention within ID15 catchments

GEUS

N-Retention

- focus on clay dominated – shallow dynamic systems

- Spatial variation in drain fraction and riparian overland flow

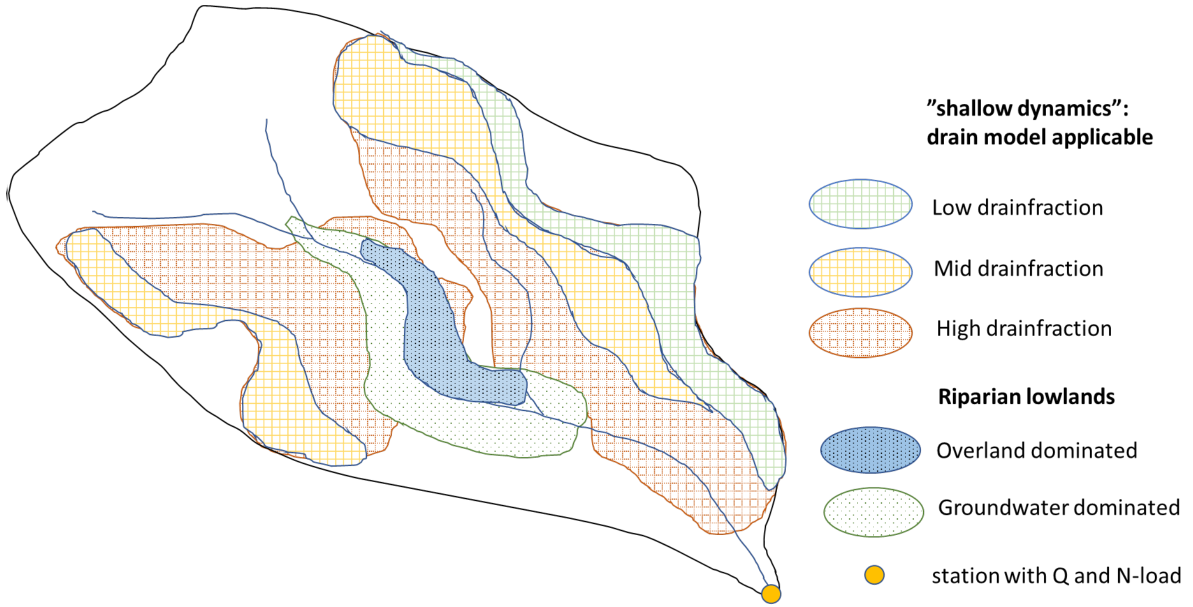

Figure 1. Concept of the application of the drain model to an ID15 catchment.

- Goal:
- Mapping variation in drain fraction within ID15 catchments
- Mapping variation in overland flow fraction in riparian zones
- Improve representation of drain flow in the DK-Model/N-Model
- Improve mapping of N-retention potential and its components
- Better impact assessment and optimization of N-reduction measured

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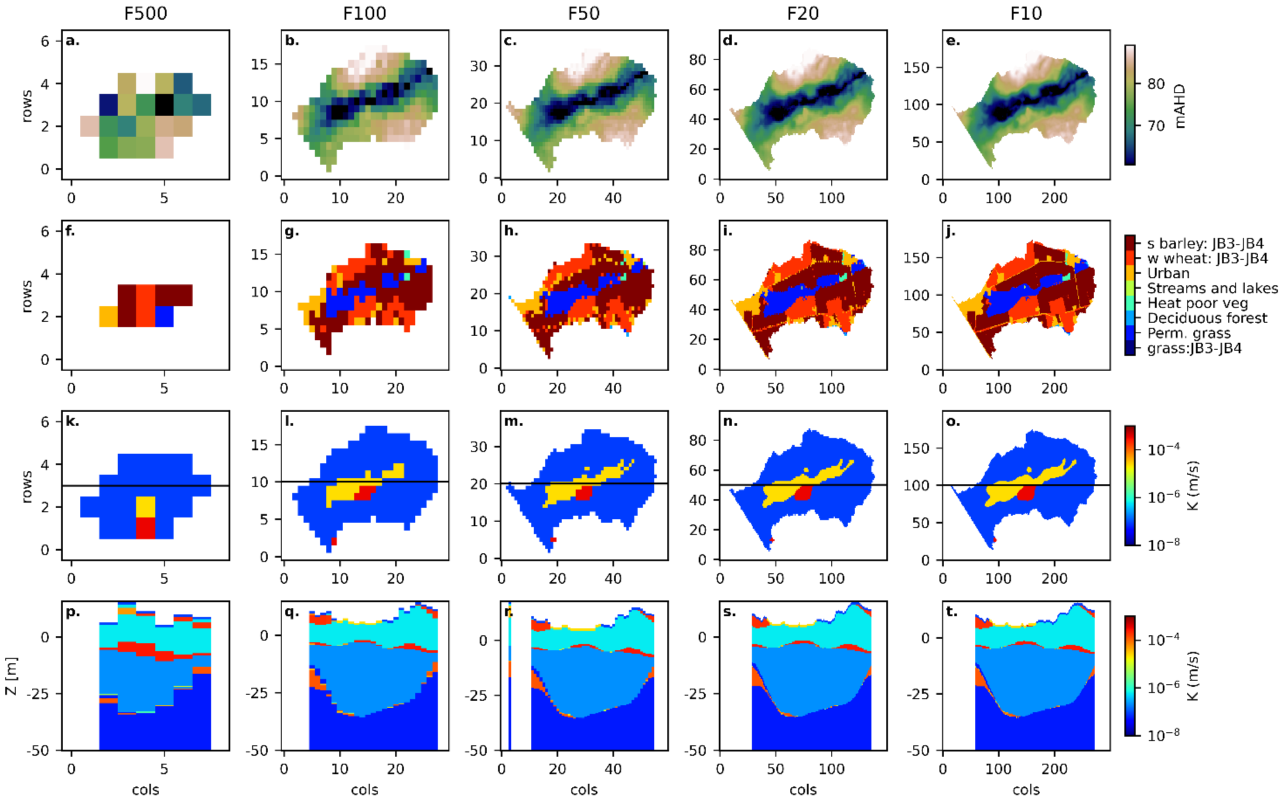
Methods

Precondition:

- Coarse-scale physically-based flow models
  - We don’t expect to represent the processes correctly
- Small observational data sets
  - We cannot make empirical prediction models

Solution:

- Fine-scale physically-based flow models
  - Cal/val against observation data
- Model-generated training data
  - Assuming we can represent the processes right at high resolution
  - Produces large amounts of data
- Machine learning as a tool to build prediction models based on large datasets



Noorduijn et al 2021, Journal of Hydrology

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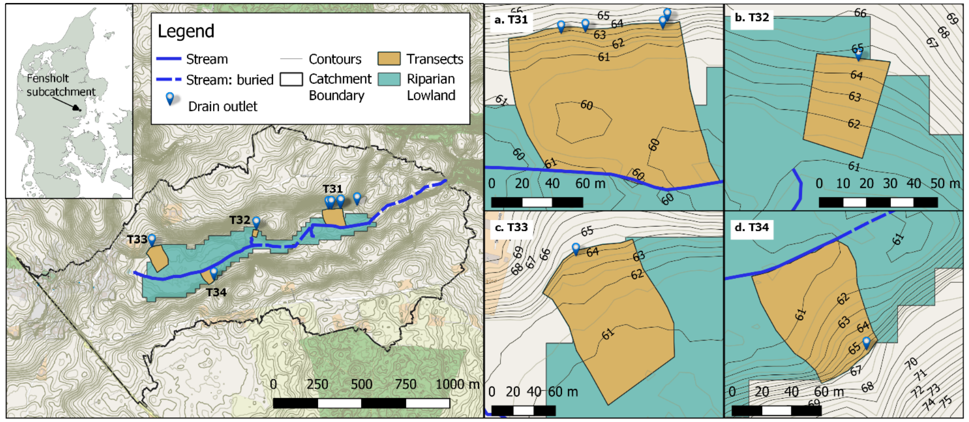
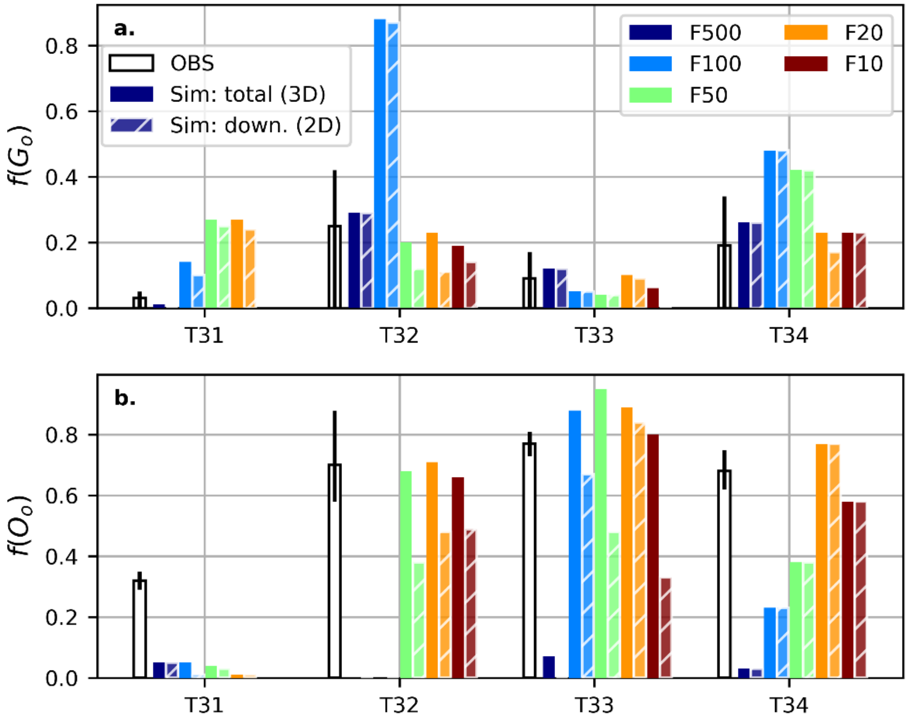
Methods

Overland flow

- Validate fine-scale physically based flow model for fieldsites
- Statistical perturbation of model
- Model-generated training data
- Machine learning based prediction model





Noorduijn et al 2021, Journal of Hydrology

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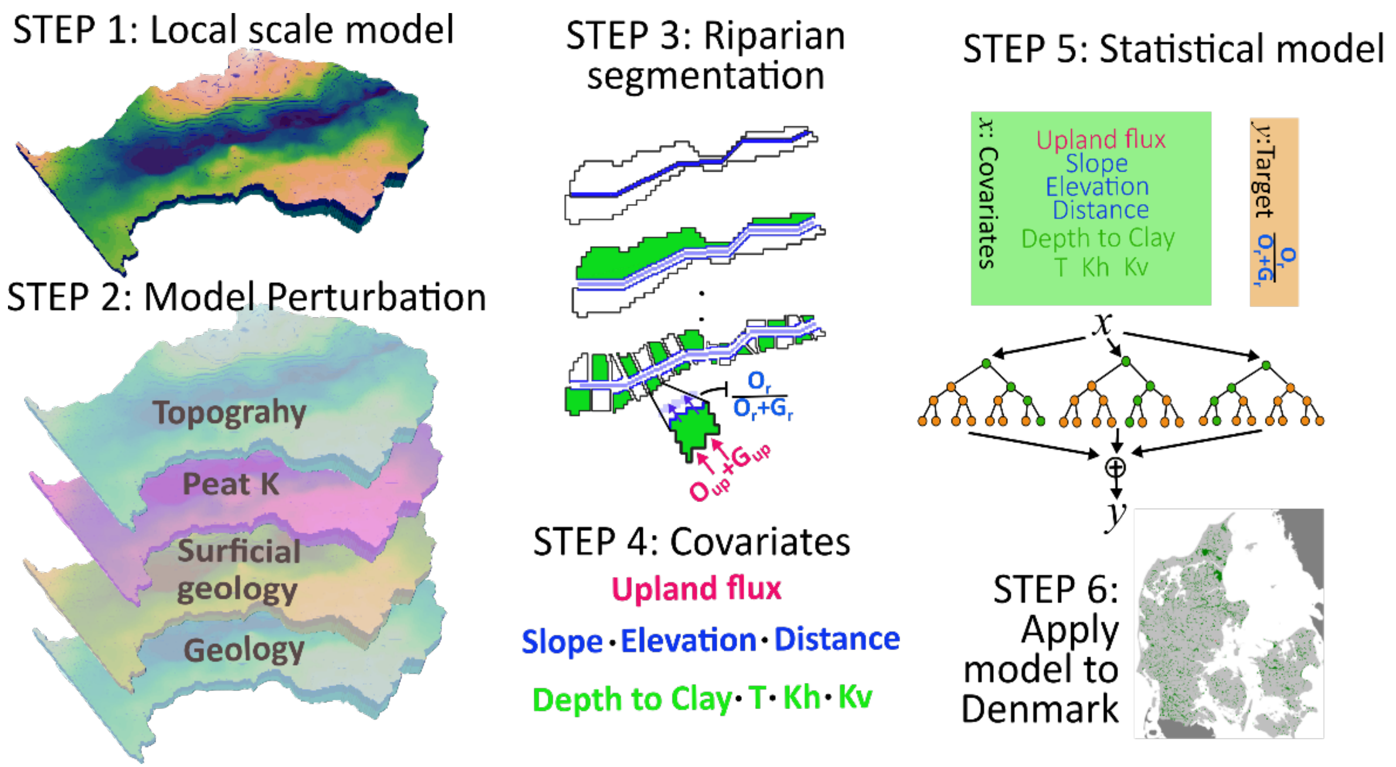
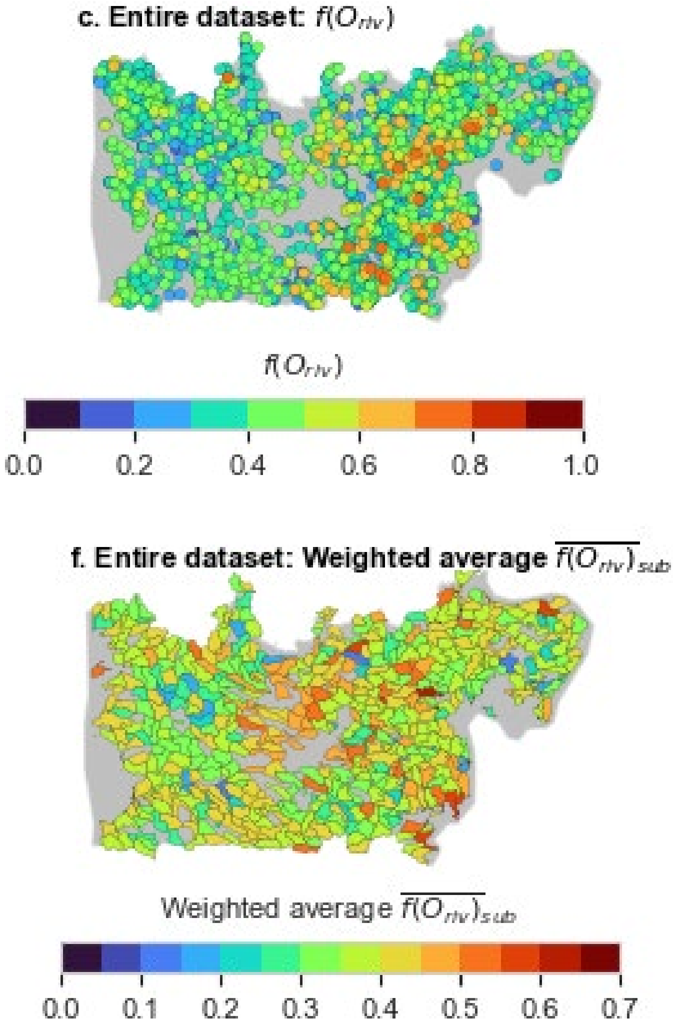
Overland flow fraction in the riparian zone $f(O_{riv})$

Saskia Noorduijn



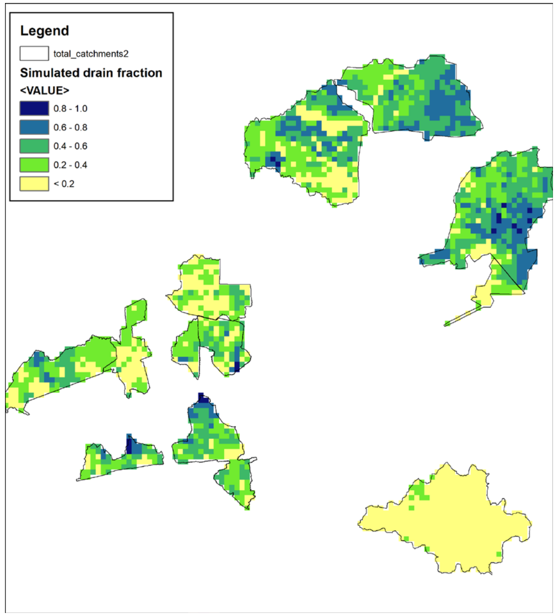
Noorduijn et al 2021, In Prep

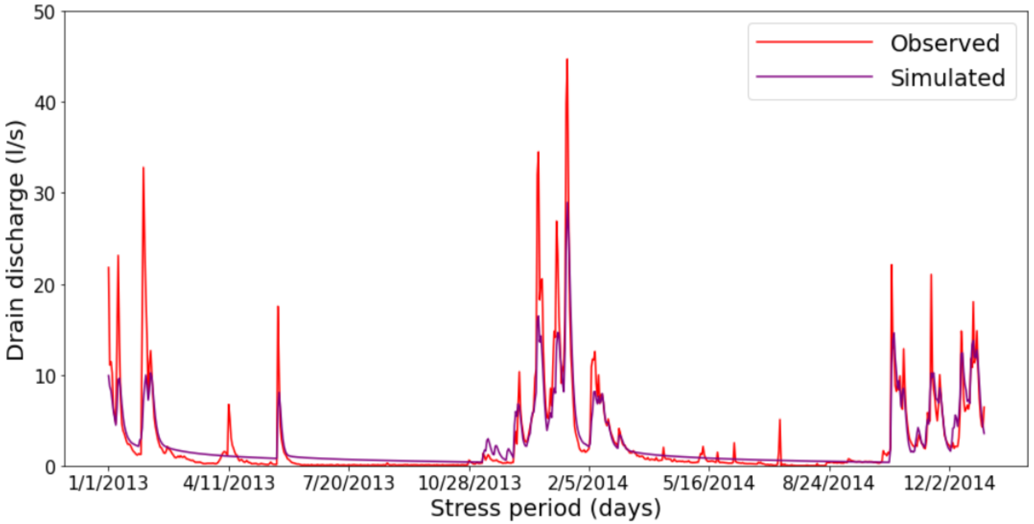


Methods

Drain fraction

- Calibrate and validate fine-scale physically based flow models from 30 drain catchments
- Supplement with additional ungauges drain catchments
- Generate modelbased training data at high resolution
- Machine learning based prediction model





Mahmood et al 2021, In Prep

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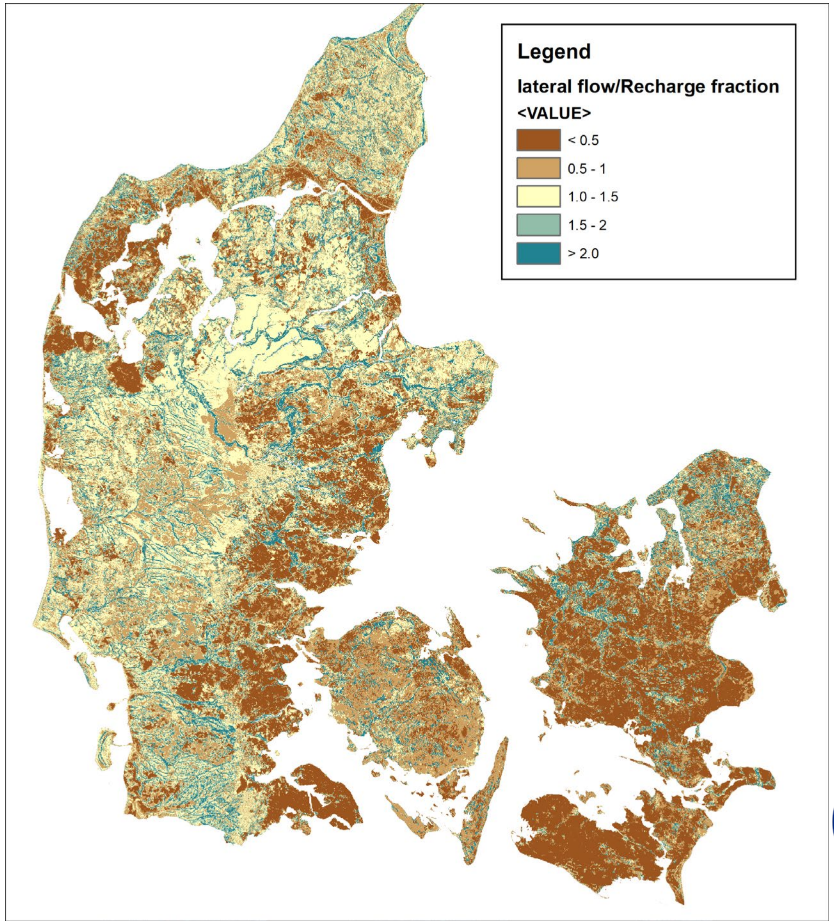
Drain fraction on clay soils f($drain_{clay}$)

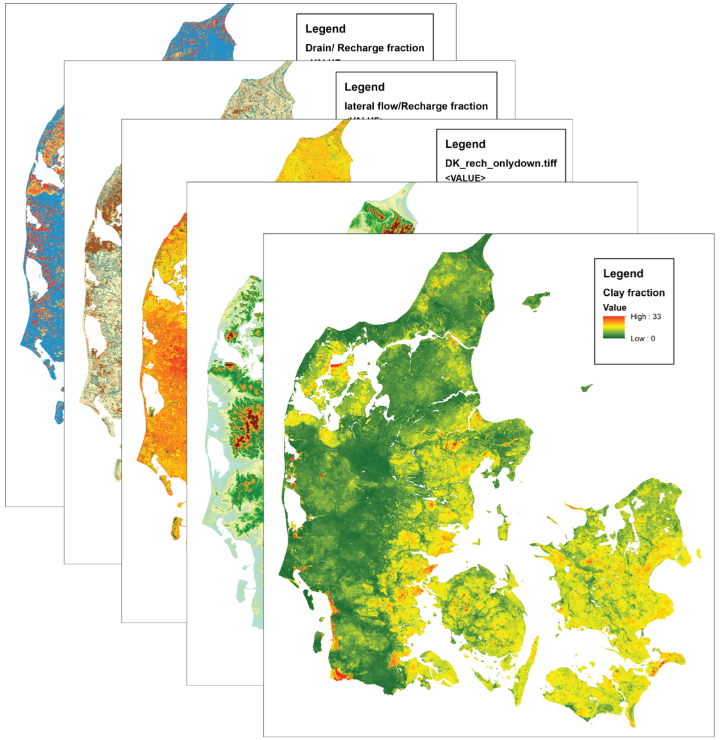
Raphael Schneider and Hafsa Mahmood

- Mapping of drainfraction from field scale to high resolution DK scale
- Generate training data from many drain submodels (Hafsa)
  - High resolution (10 m) - thousands of datapoints
- Sample in national variability
  - Geology, topography, recharge
- Select co-variates available nationally at high resolution (10-30 m)
- Create a machine learning model for predicting f($drain_{clay}$)
- Investigate seasonal dynamics of drainfraction

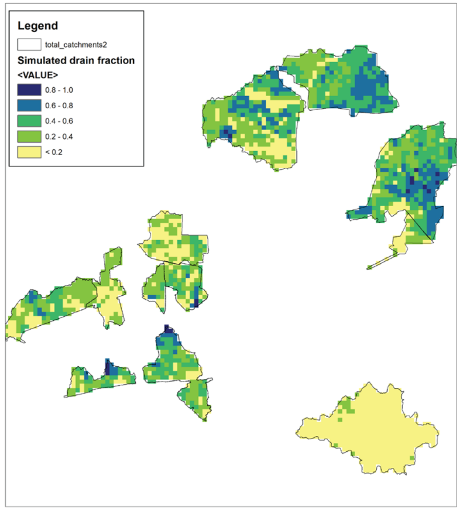


Drain fraction on clay soils f($drain_{clay}$)

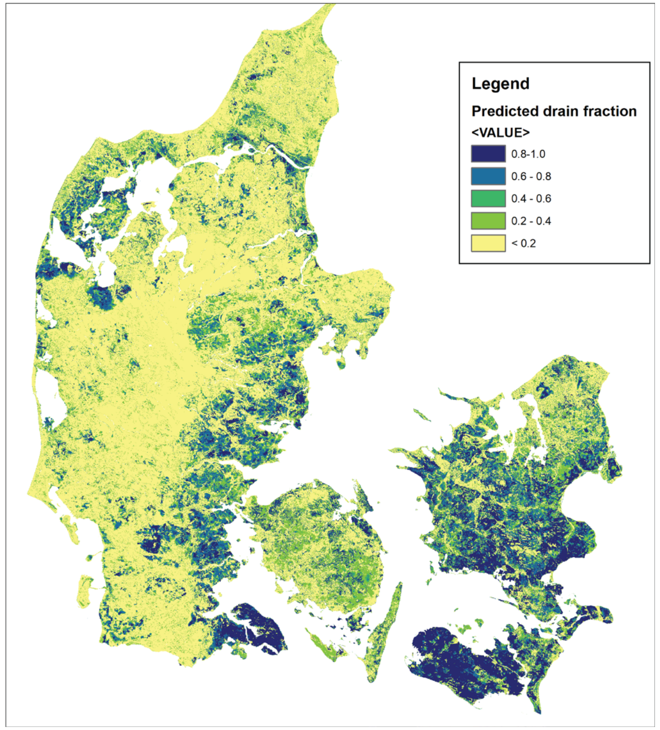
Co-variates



Training data



Machine Learning Prediction



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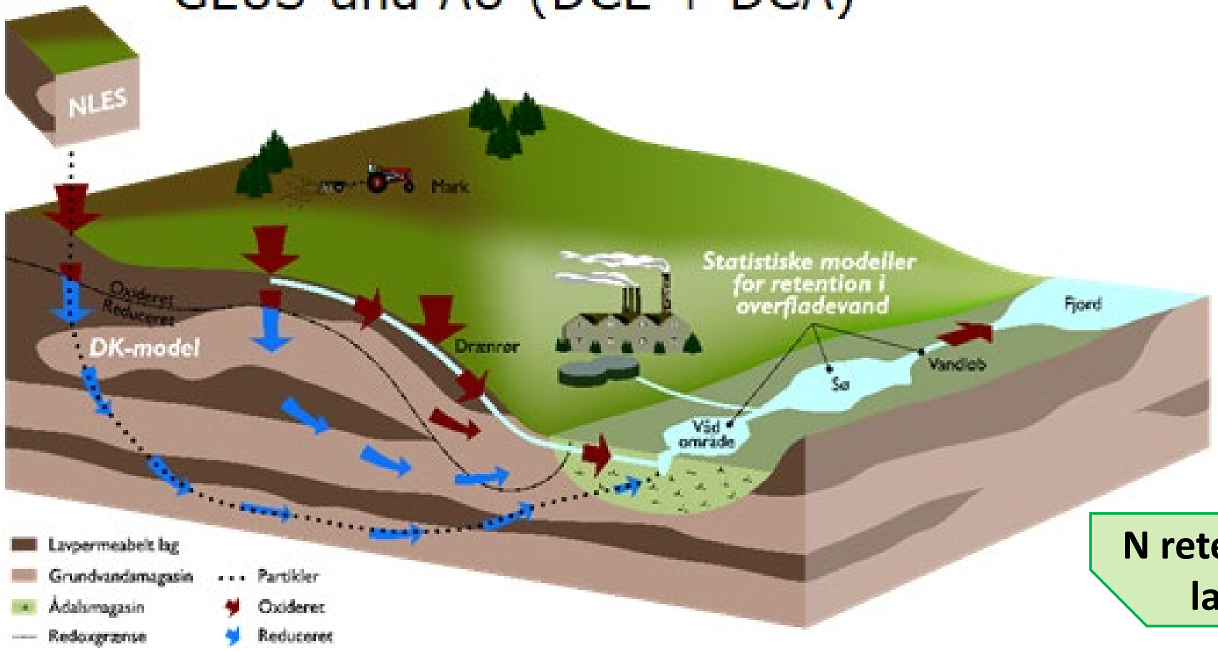
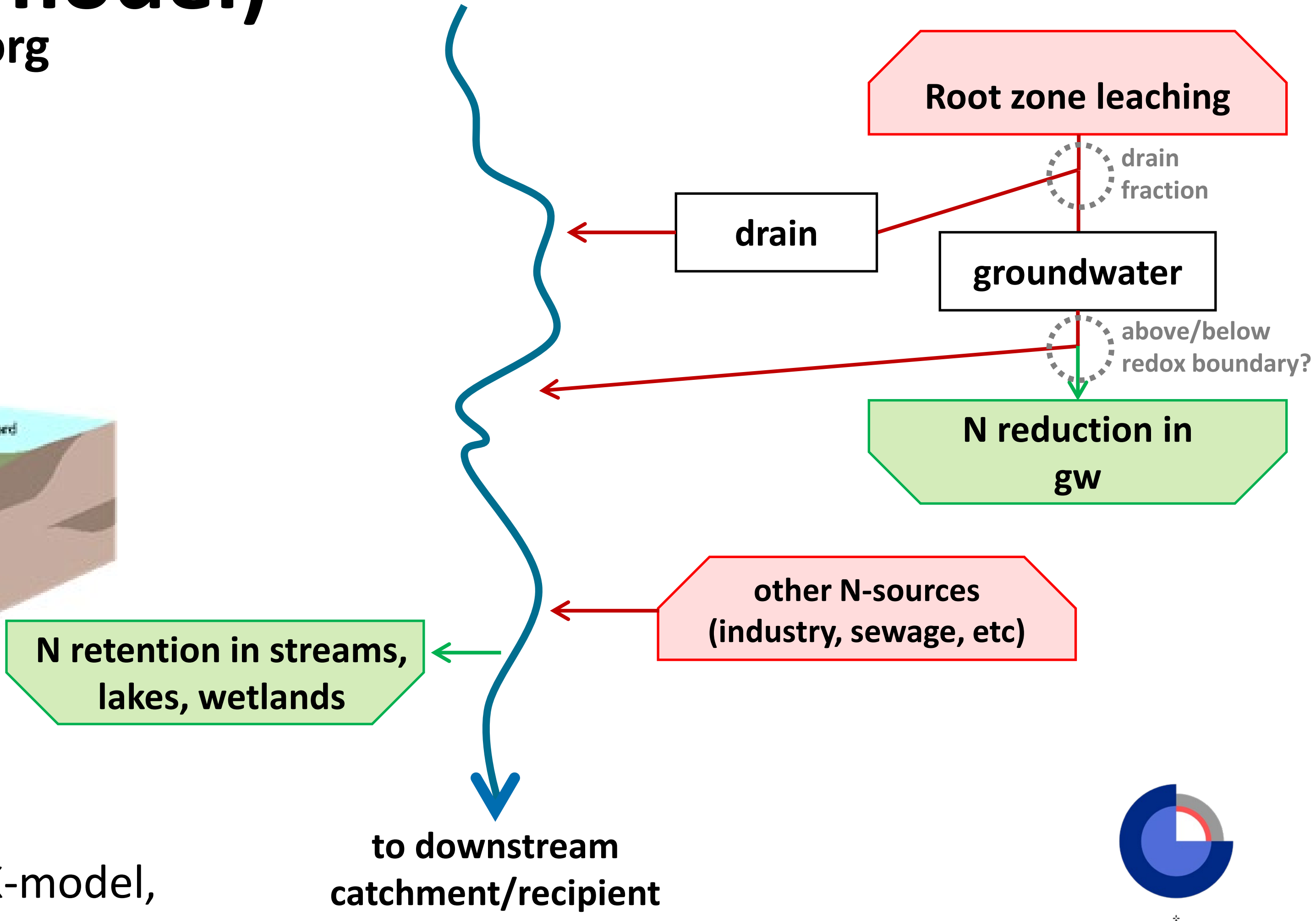
Improvement of the DK-model and national nitrogen model (N-model)

Raphael Schneider and Lars Troldborg

GEUS and AU (DCE + DCA)





Currenty run with 500m DK-model,
N retention results delivered at
ID15 scale (retentionskort)

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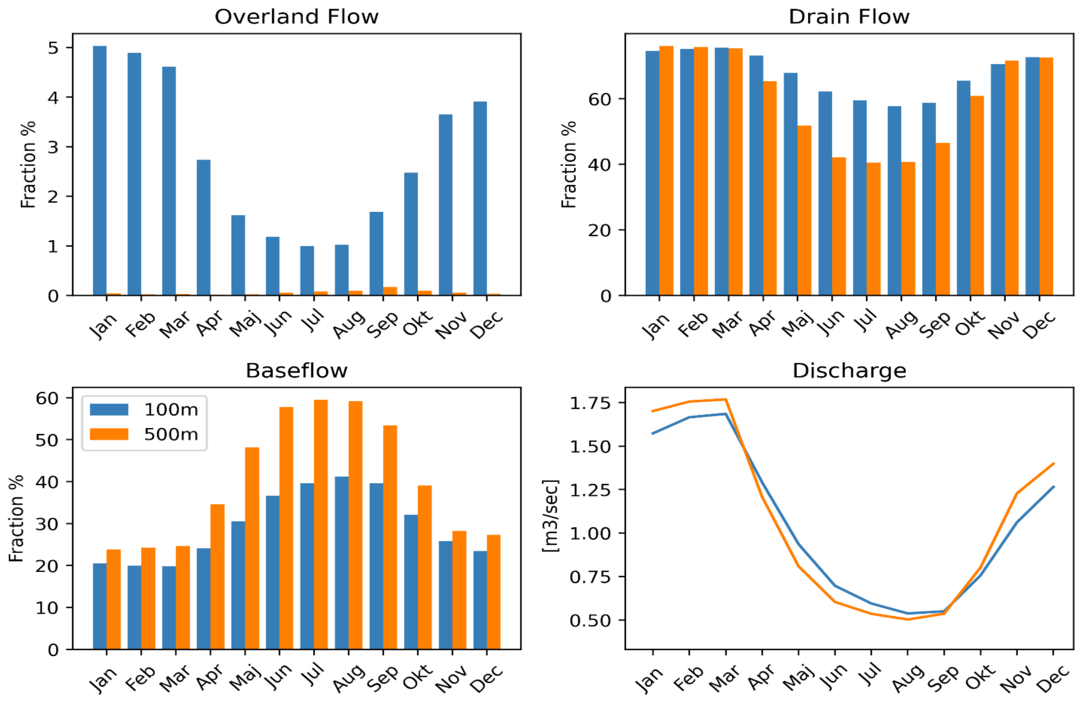
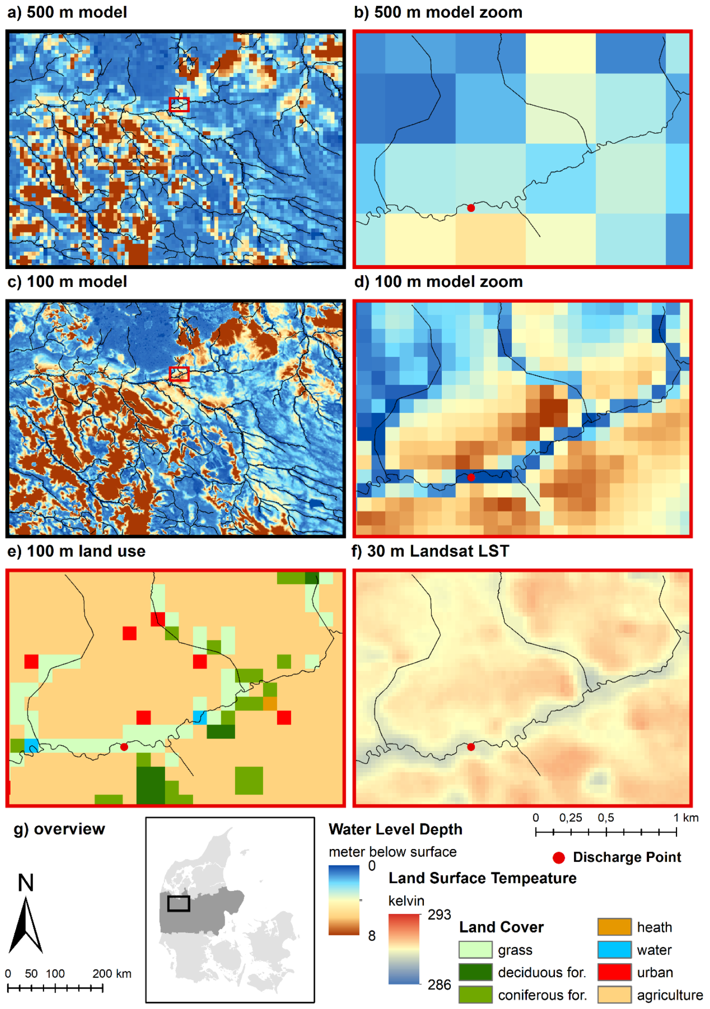
Improvement of the DK-model and national nitrogen model (N-model)

1. Run a submodel of the N-model based on the **100m** DK-model (Skjern Å headwater)





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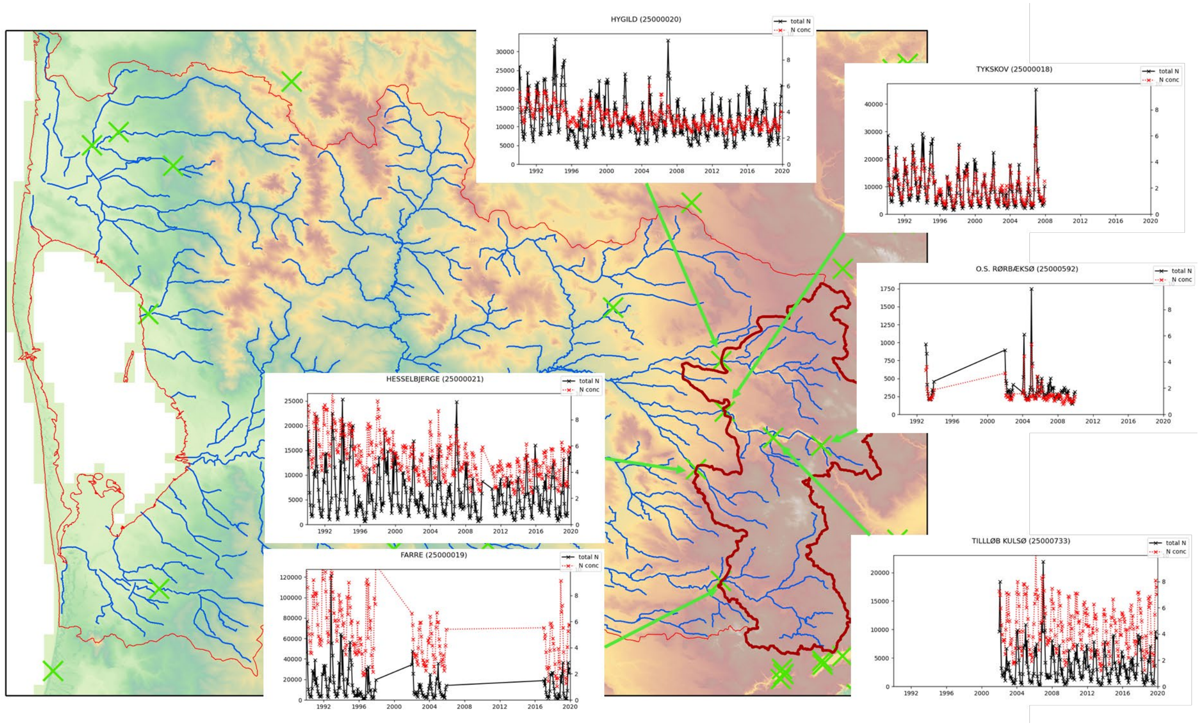
Improvement of the DK-model and national nitrogen model (N-model)

1. Run a submodel of the N-model based on the **100m** DK-model (Skjern Å headwater)
2. Improve DK-model drain simulation aided by **ML drain fraction map**
3. (potentially) Include differentiated **N-reduction potential in riparian zones**/wetlands



Test Skjern Å N-model setup at each step against observed N loads

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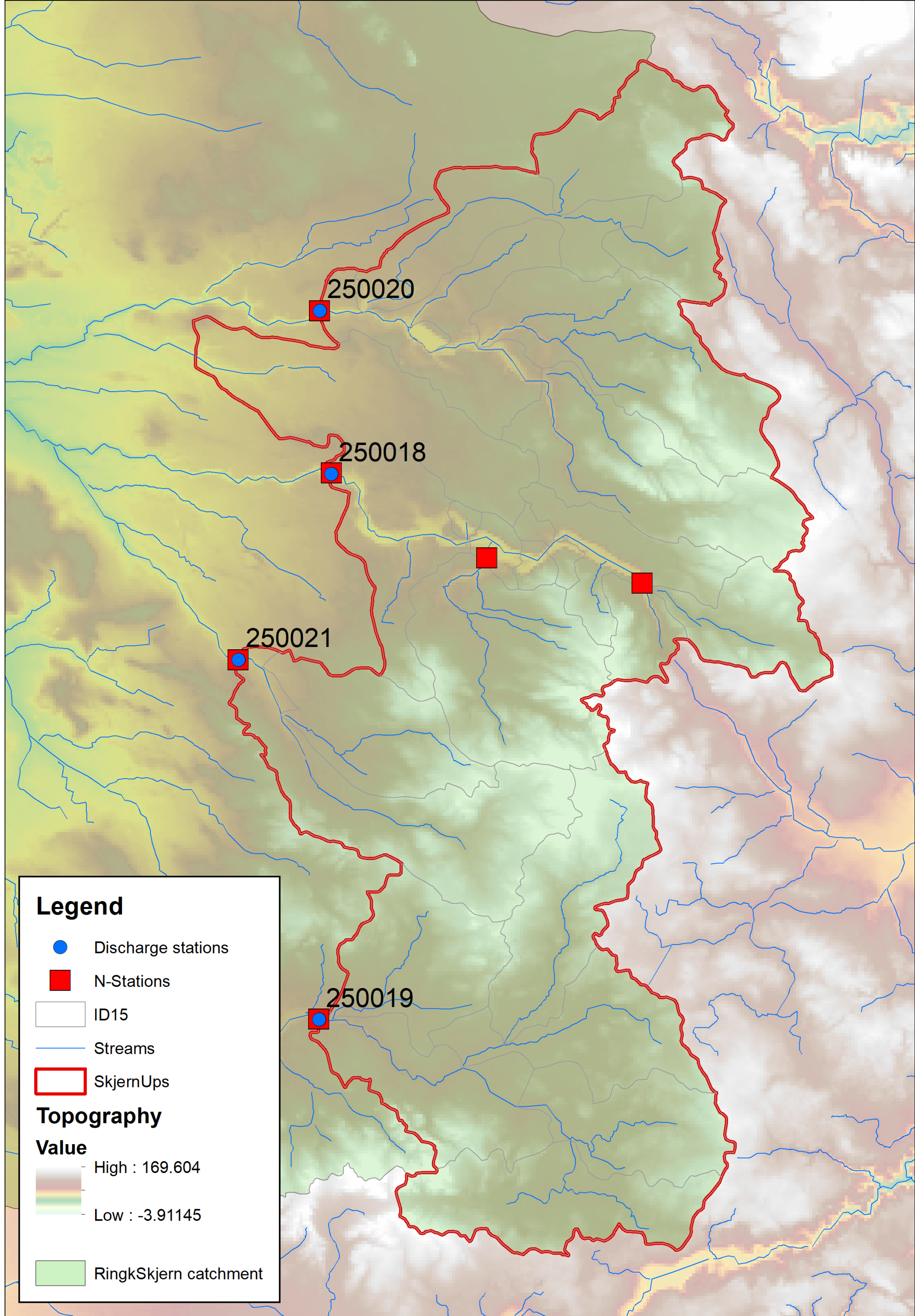
Skjern Å headwater model

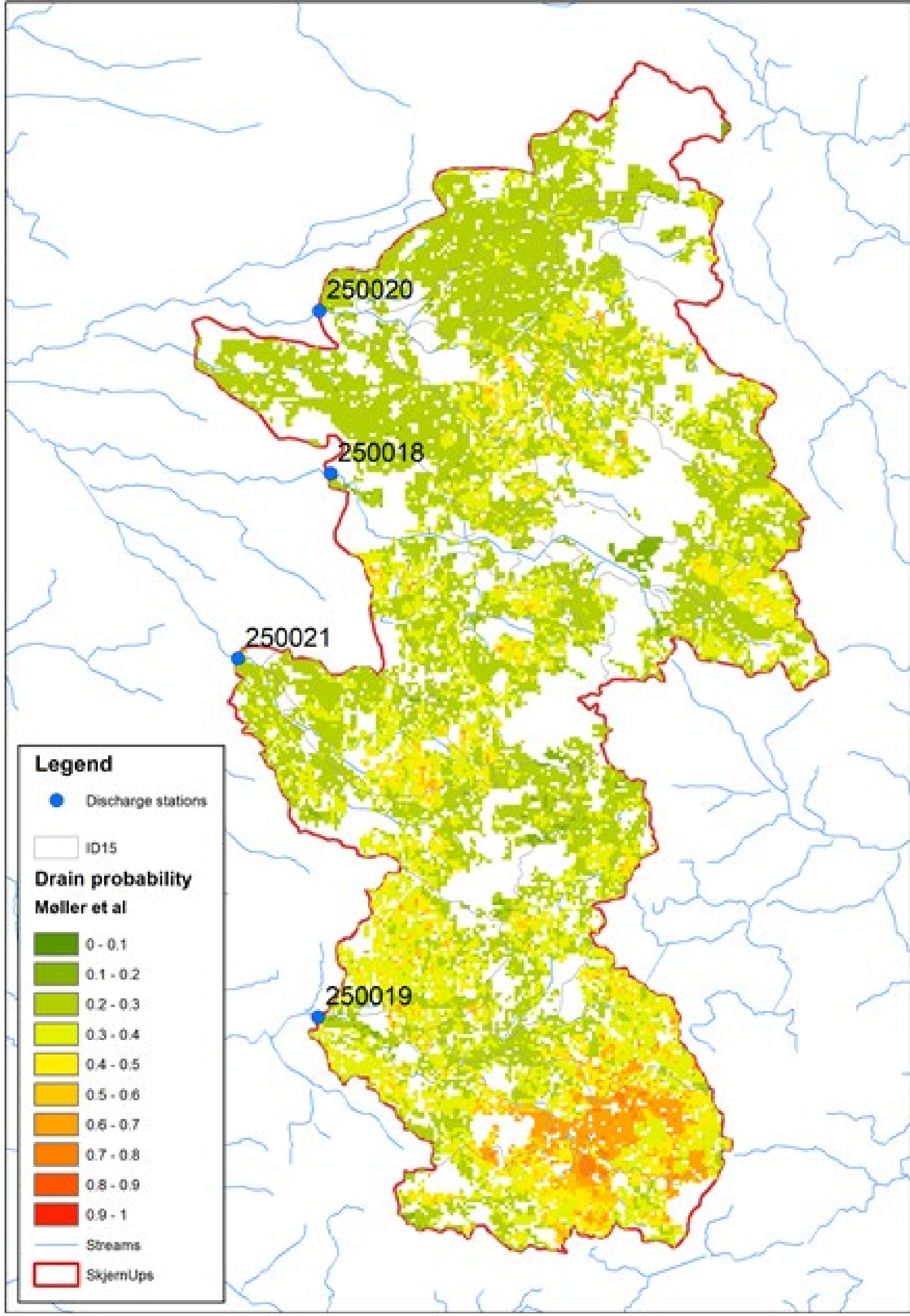
Streamflow performance at 4 outlets

	NSE	fbal
Q250018	0.66	0.05
Q250019	0.76	-0.18
Q250020	0.82	0.04
Q250021	0.43	0.27
average	**0.67**	**0.05**



Skjern Å headwater model

Probability for artificial drain, as predicted by machine learning algorithm (Møller et al. 2018)

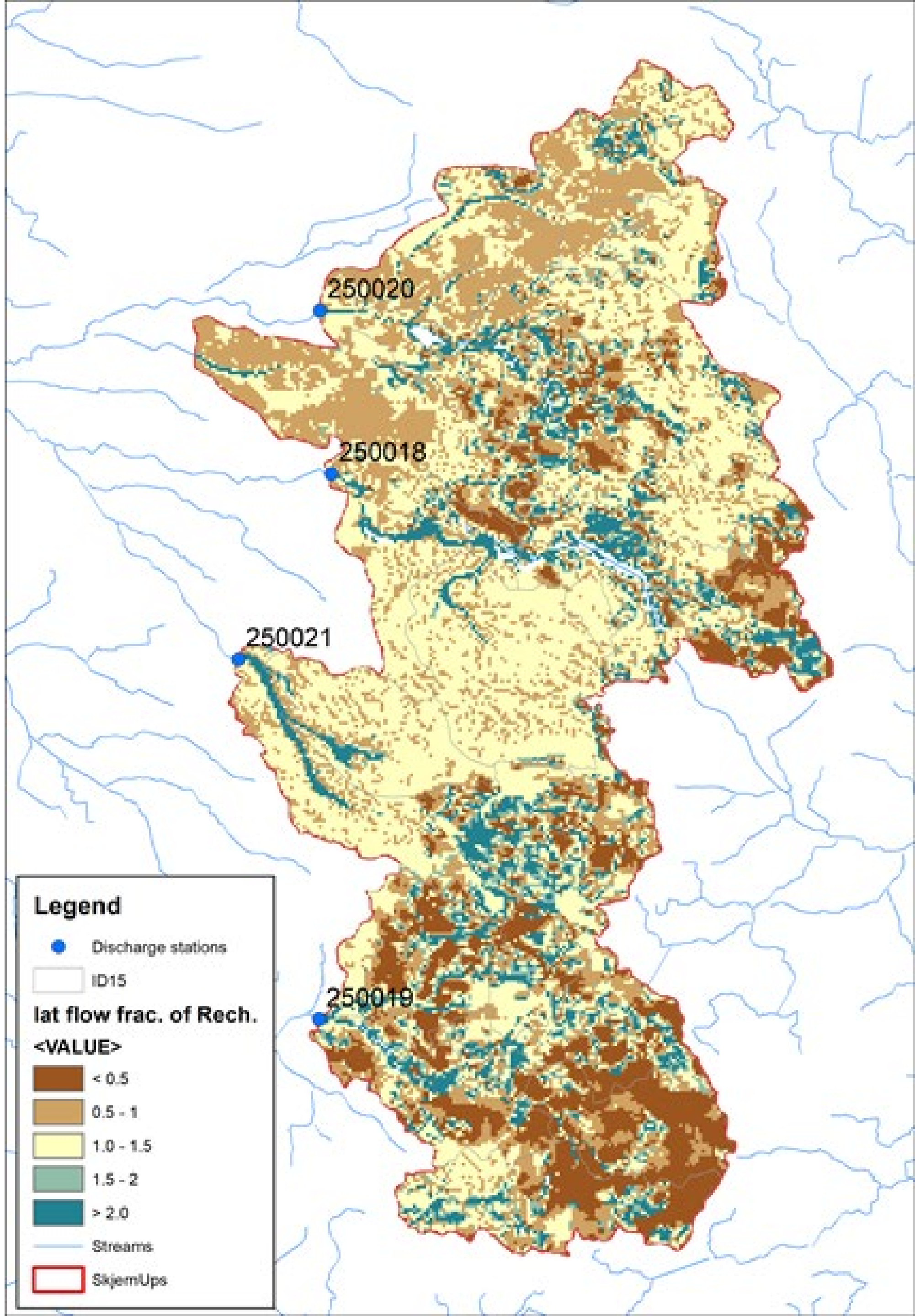


Skjern Å headwater model

$$\frac{f_{lat,l1} + f_{z,l1\_l2}}{recharge}$$

Lateral flow fraction
Indicator for areas with:

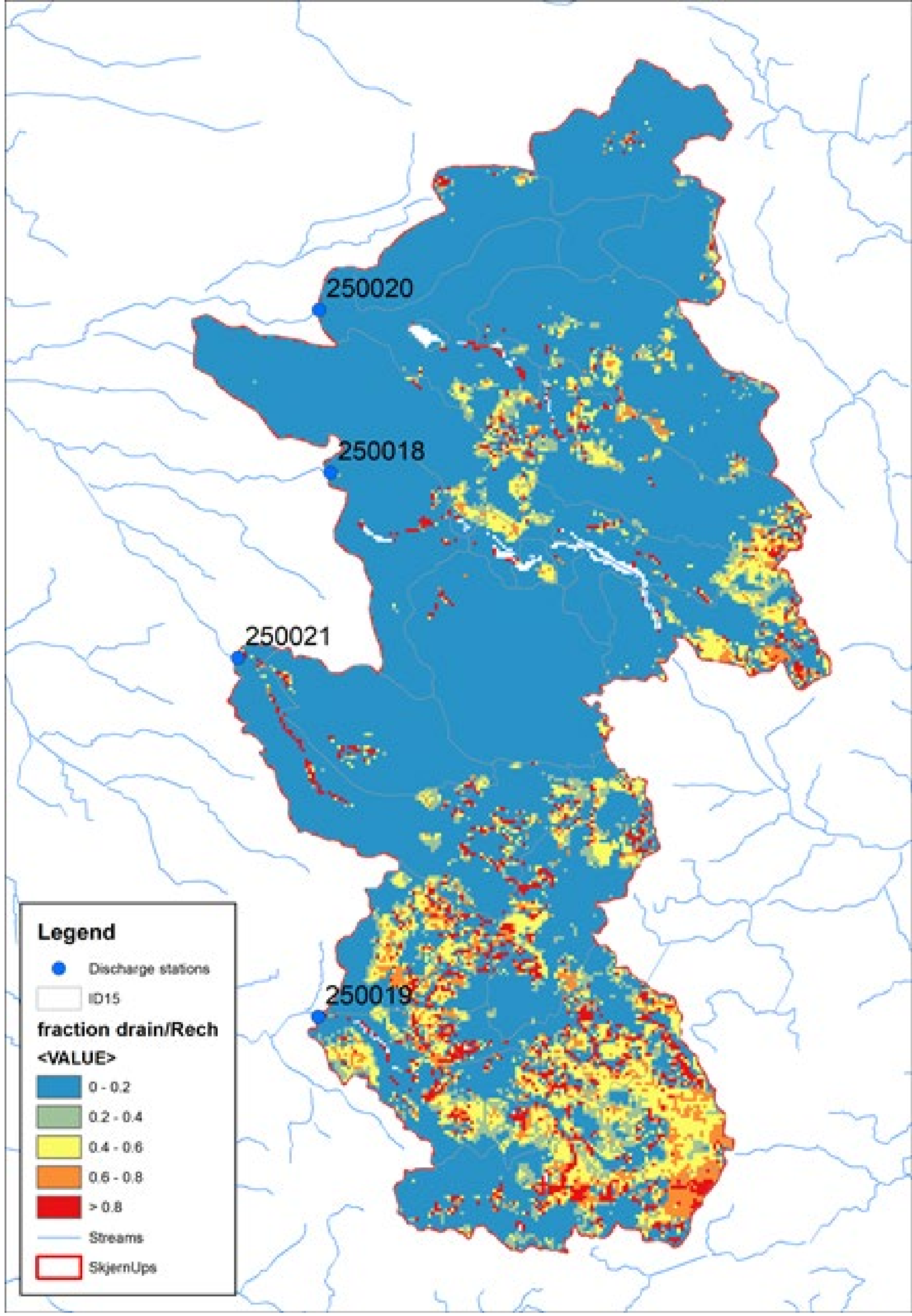
- shallow groundwater dynamics (dominated by local recharge, **low** lateral flow fraction)
- complex groundwater dynamics (dominated by lateral/regional flow, **high** lateral flow fraction)



Skjern Å headwater model

Simulated drain fraction

$$\frac{drain}{recharge}$$

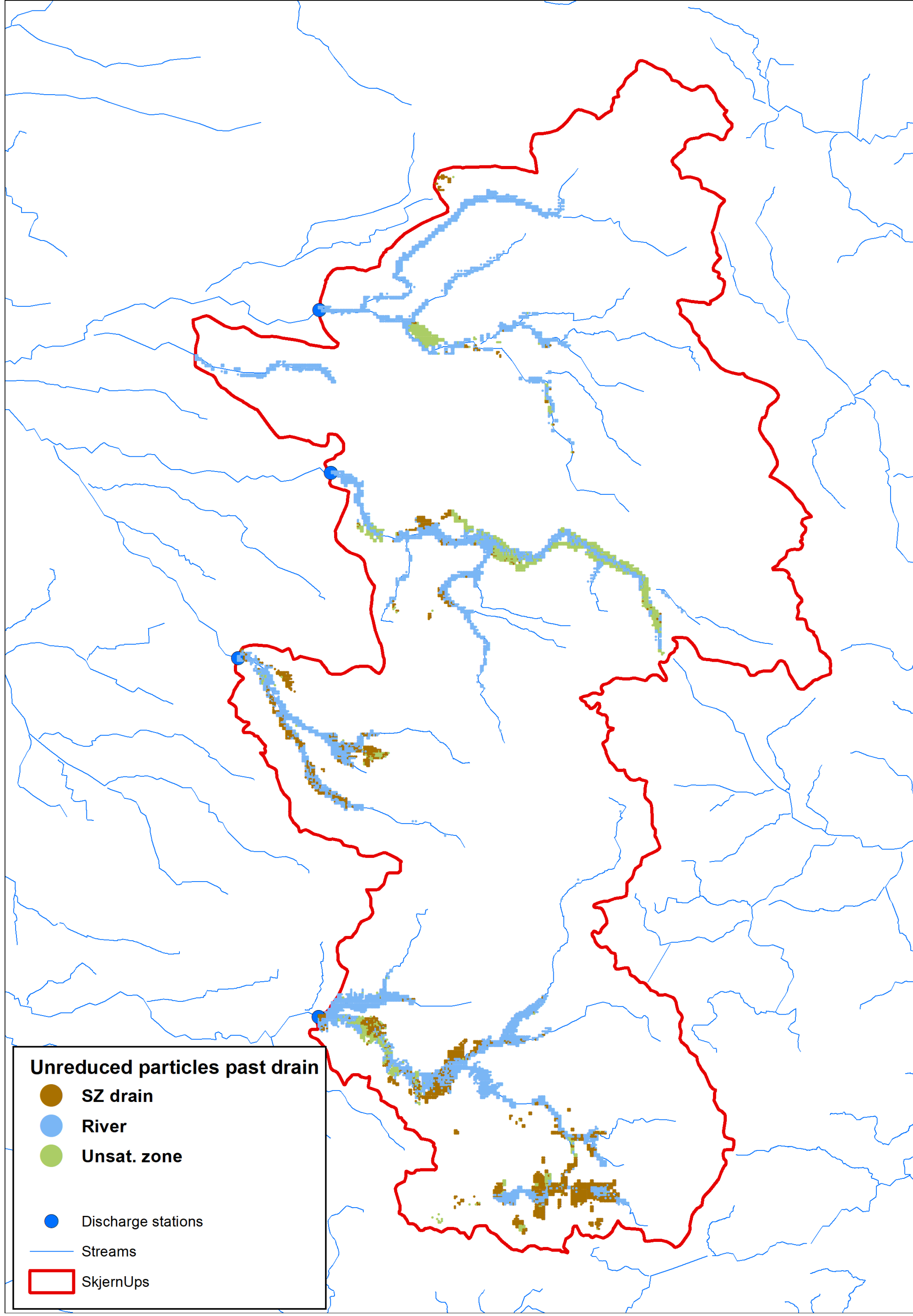


Skjern Å headwater model

First results of 100m N-model setup

uncalibrated, first results!

Displaying origin of particles ***below drain*** that reach recipients without being reduced in groundwater



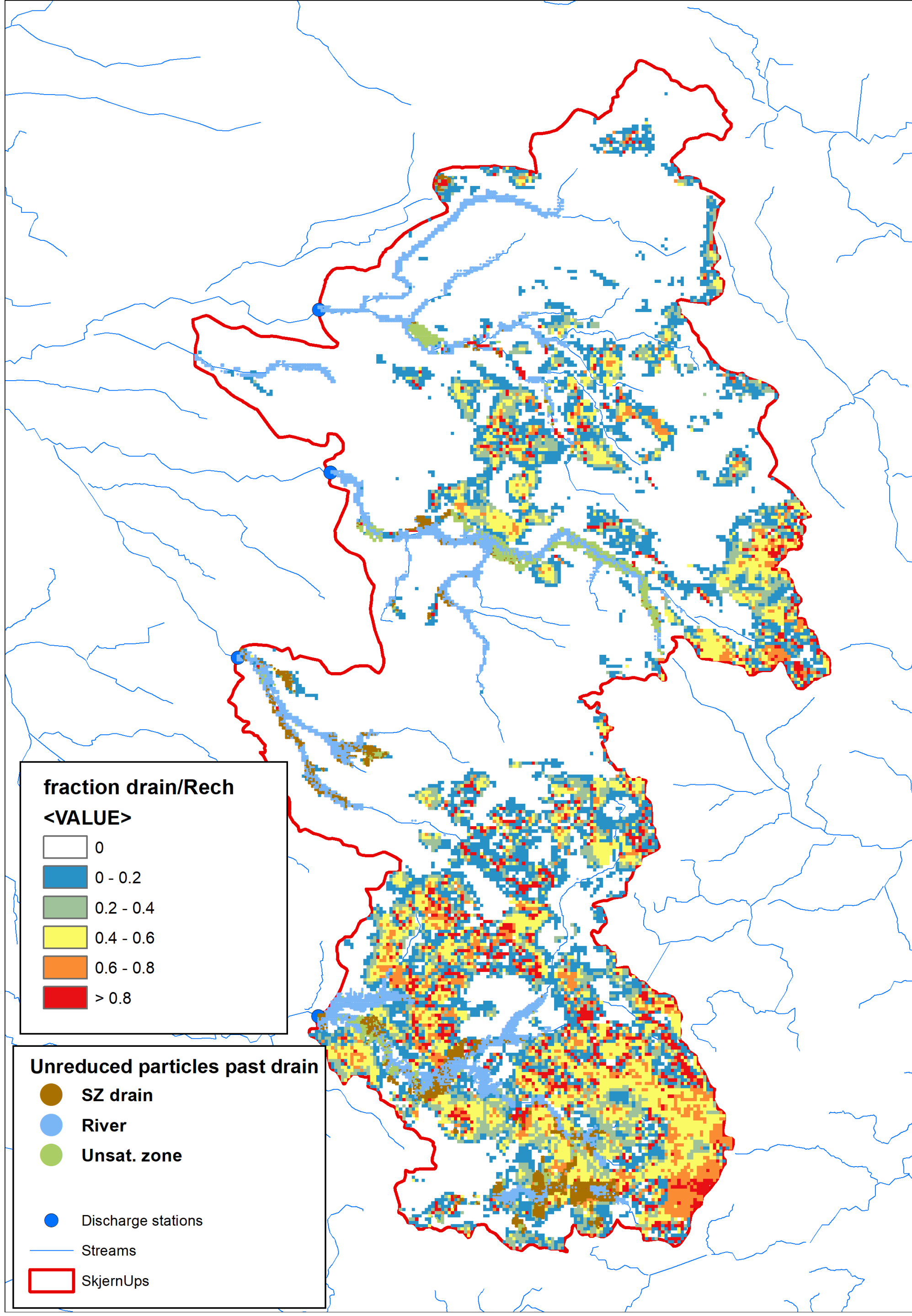
Skjern Å headwater model

First results of 100m N-model setup

uncalibrated, first results!

Displaying origin of particles ***below drain*** that reach recipients without being reduced in groundwater

Diplayed with drain fraction, which is used to partition N-leaching from rootzone (drain being **not** reduced)



Next steps

- Collaborate with AU/Hafsa on Mike SHE drain models and calibration

- Based on Hafsas simulations build machine learning model for predicting drain fraction

- N-Model 100m for Skjern Upstream
- Compare and adjust to N-observations

- Utilize the drain fraction mapping to improve drain simulations in the N-model for Skjern Upstream

- Deliver initial distributed N-retention map for Skjern Upstream

- Deliver updated distributed N-retention map for Skjern Upstream

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