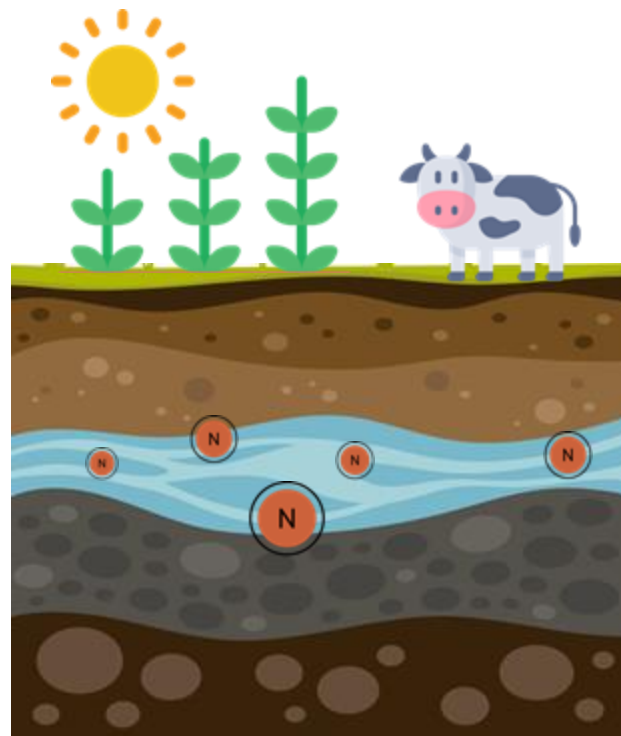


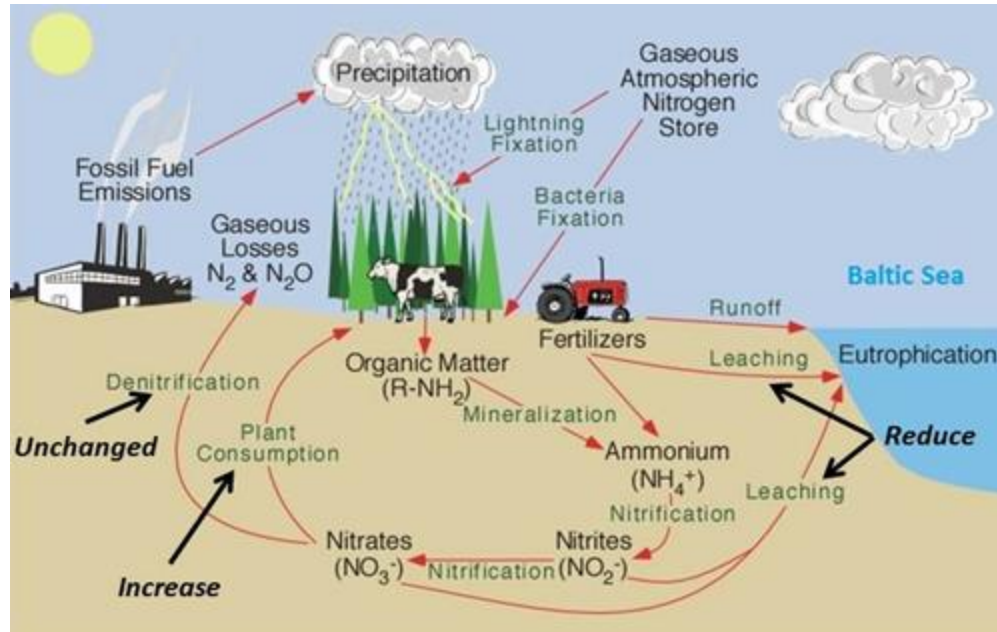
# Spatial Modeling of Nitrate Leaching in the Netherlands

AI-driven Data Engineering and Reusability for Earth and Space Sciences (DARES) @ ECAI 2025



# 1. Motivation

- Nitrate leaching** → The process of **washing nitrogen out** through the soil with water.
- Happens when the soil contains **more nitrate than plants can absorb**.



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Why is it a problem?

- Leads to **groundwater pollution**
- Causes algal blooms and fish die-off
- Risks **public health** (e.g., blue baby syndrome)

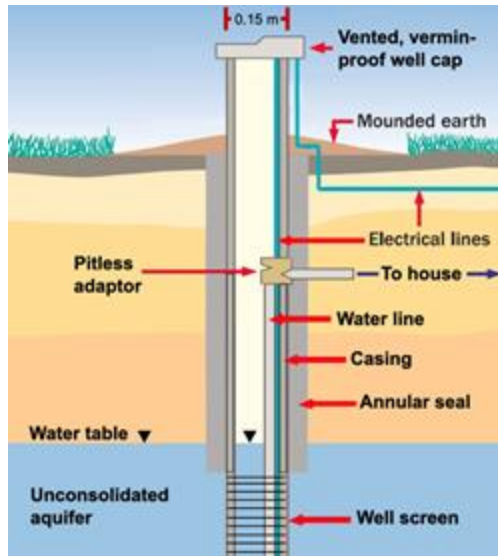


Algal bloom

Source:  
<https://nypost.com/2018/06/22/toxic-algae-blooms-becoming-more-common-across-us/>

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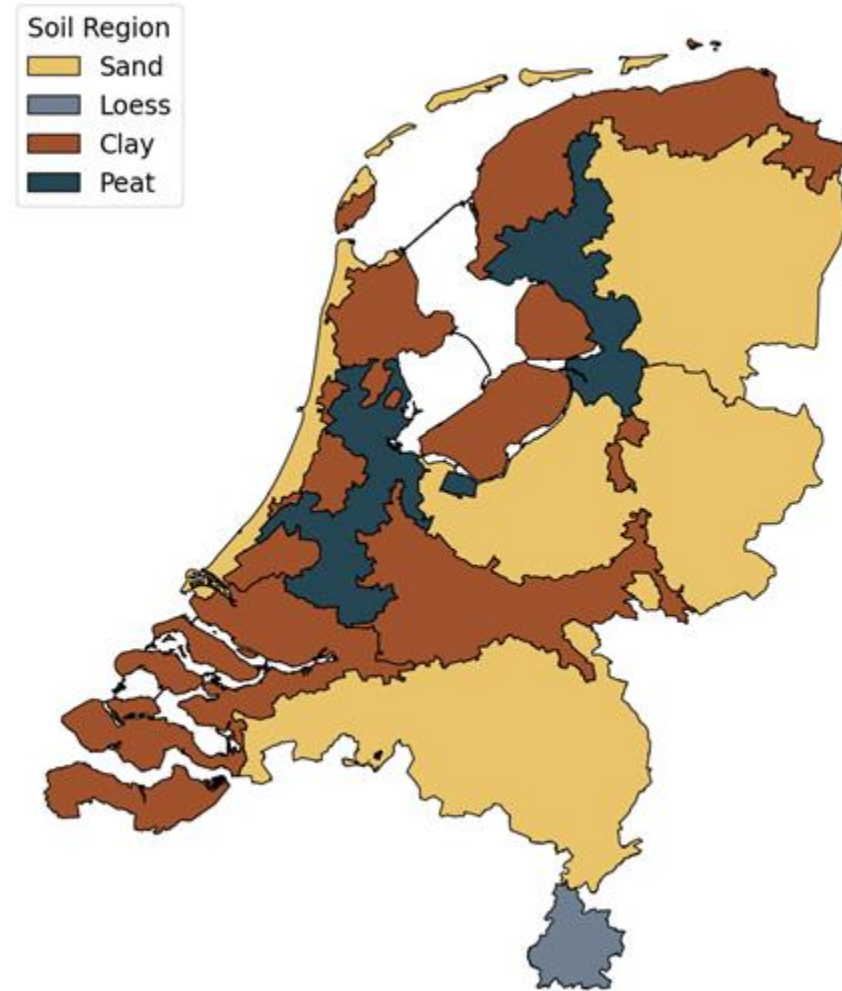
- Nitrate leaching** → The process of **washing nitrogen out** through the soil with water.
- Happens when the soil contains **more nitrate than plants can absorb**.
  - Can be monitored by **sampling groundwater** through monitoring wells.



# 1. Motivation

Relevance for the Netherlands:

- **66%** of the land area is used for **agriculture** [1]
- Highest **livestock density** of EU countries [2]
- High **fertilizer** usage [3]
- **Sandy soils** (50% of area) provoke nitrate leaching [4, 5]



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## Objective:

- To develop an **explainable spatial regression model** for predicting nitrate concentrations in groundwater in **the Netherlands**, using spatial and environmental factors.

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- To develop an **explainable spatial regression model** for predicting nitrate concentrations in groundwater in **the Netherlands**, using spatial and environmental factors.

## Challenges:

- Monitoring wells are **sparse** → many areas with **no direct data**
- Groundwater sampling is **expensive** → **low sampling frequency**

## 2. Literature review

*"Everything is related to everything else, but near things are more related than distant things."*

— *Waldo Tobler's First Law of Geography (1970)*

Traditionally **spatial** and **temporal autocorrelation** is used.



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Relying on geographic proximity and may omit environmental interactions involved in nitrogen cycle:

- ❖ **Spijker et al. (2022):** → Introduced environmental variables  
→ Developed **Random Forest model**

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### Limitations addressed:

- a. Limited temporal scope — only year 2017 was analyzed
- b. Missing key nitrogen cycle factors – explained **58% of variance**
- c. Used only **model-specific** interpretability

# 3. Methods

## a) Study Area & Time Period

- 12 provinces
- City regions are excluded
- Years: 2008 - 2023



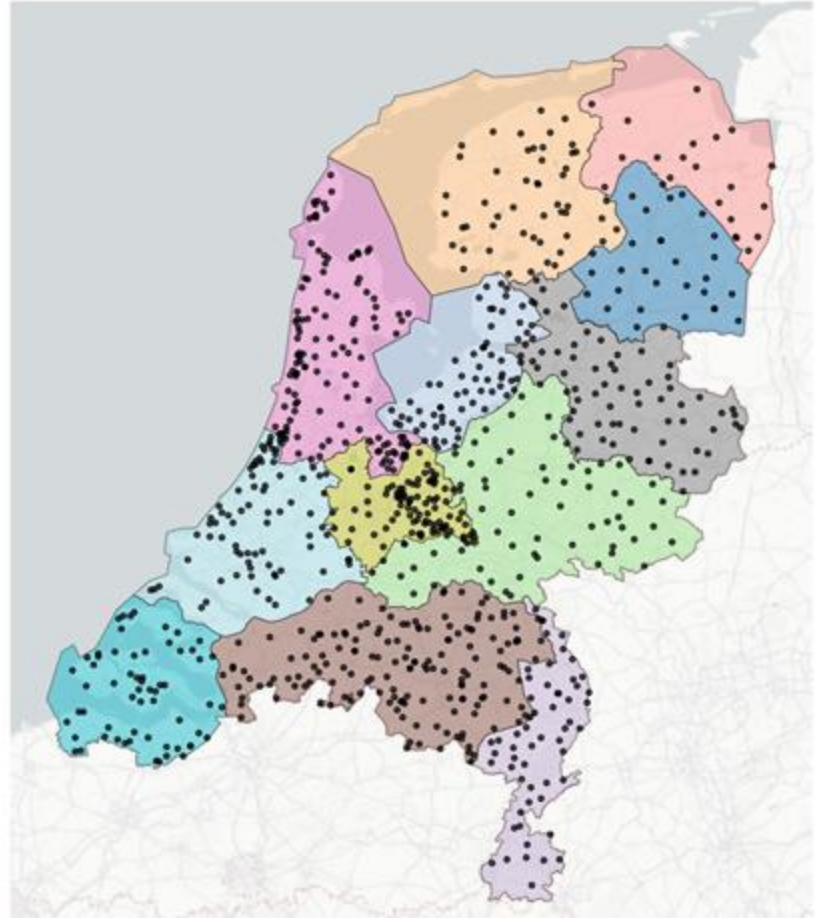
# 3. Methods

## b) Target variable

- **Nitrate** concentration in groundwater
- ~870 locations
- Sampled about twice a year
- Source:



Basic Subsurface Registration  
(BRO)



# 3. Methods

## c) Explanatory variables

### Time Series



Temperature (KNMI)



Precipitation (KNMI)



Groundwater table (BRO)

### Spatial



Population density (CBS)



Elevation (AHN)



Land use (WER)

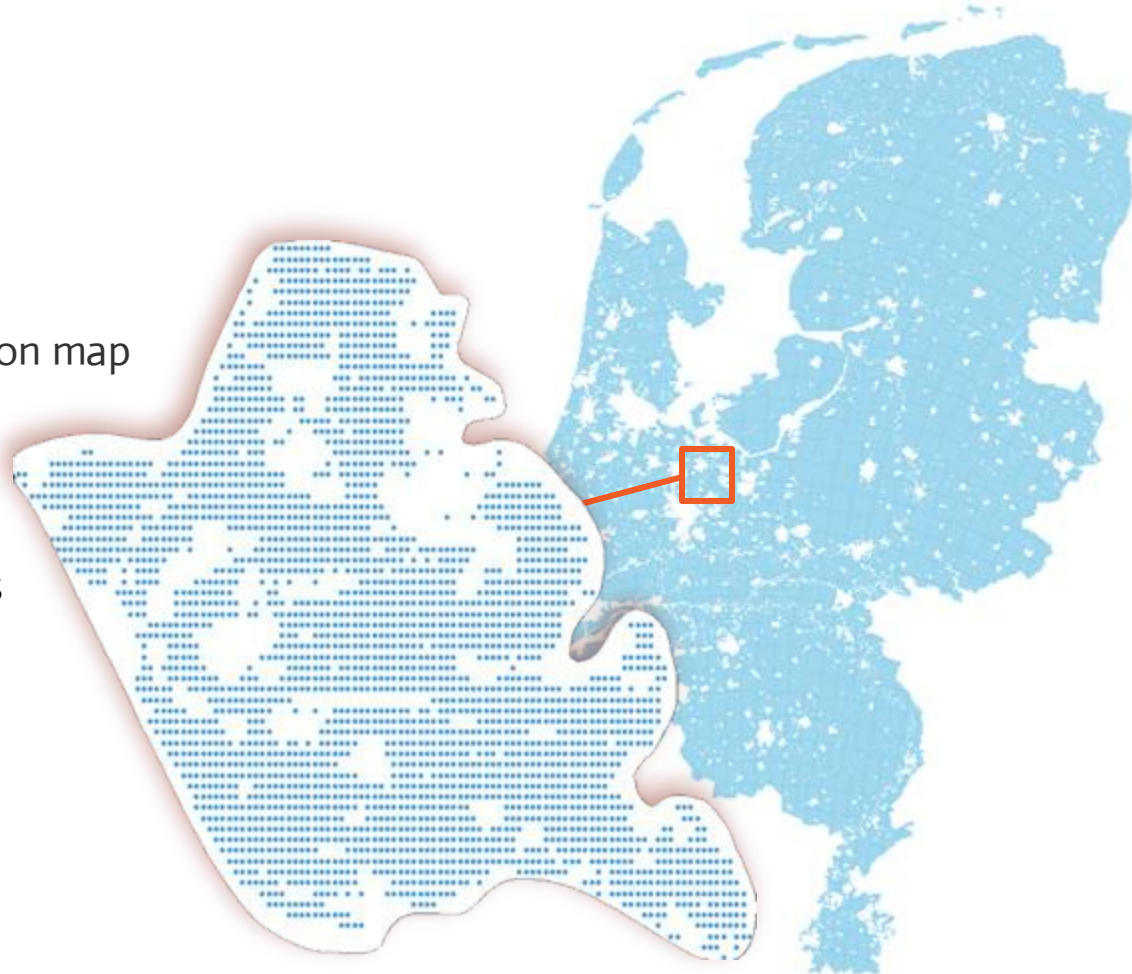


Soil and geochemical properties (BRO)

# 3. Methods

## d) Prediction grid

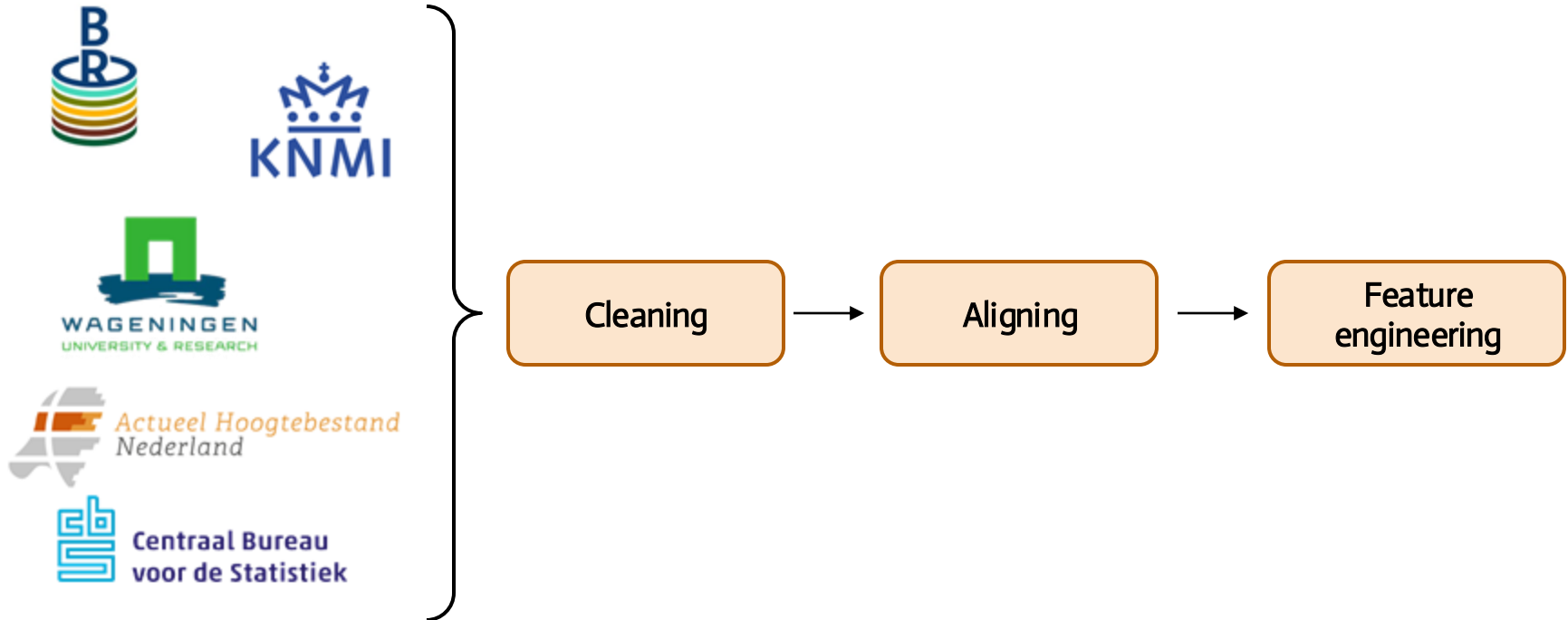
- Nationwide  $500 \times 500$  m prediction map
- Excluding city regions
- Each point  $\rightarrow$  location + date + environmental factors
- **Years:** 2010 | 2017 | 2021 | 2023



# 3. Methods

## e) Data Pre-processing

Sources:



# 3. Methods

## f) Model selection

### Ridge Regression

- Linear model with  $L^2$  regularization to prevent overfitting
- Interpretable by design

### Random Forest

- Ensemble of decision trees – non-linearity
- **Model-specific interpretability** (Gini impurity reduction)

### XGBoost (Extreme Gradient Boosting)

- Sequentially adds trees to correct previous errors
- **Model-specific interpretability** (Loss-reduction gain)



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- 
- ❖ **Model-agnostic** interpretability applied across all models.
  - ❖ **Best-performing** models combined in **Ensemble prediction**.

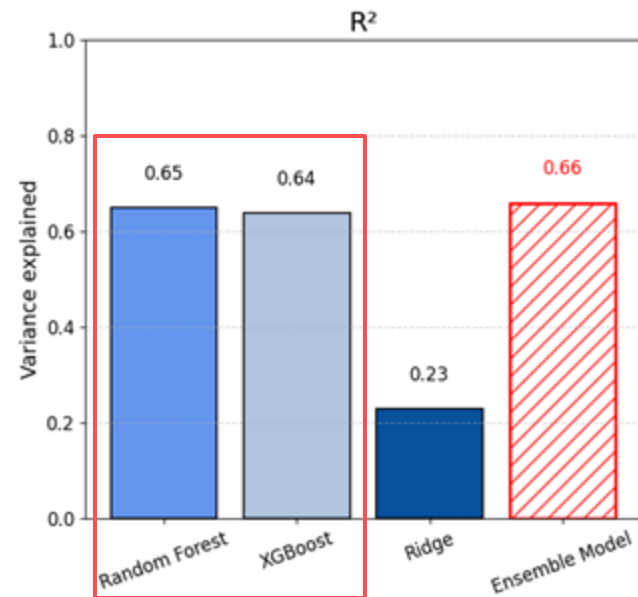
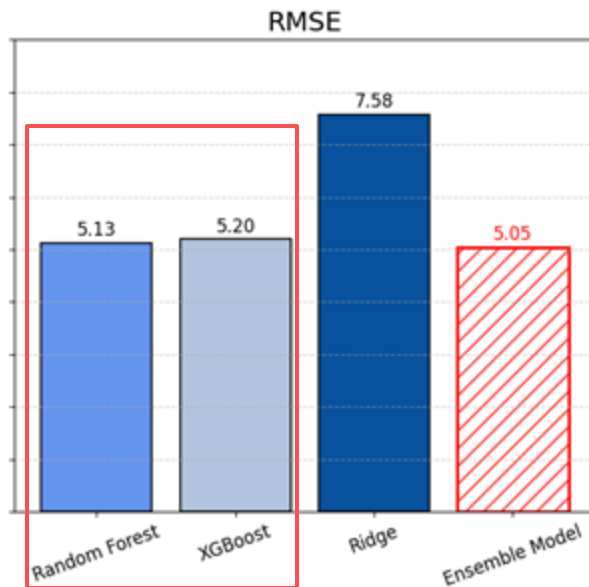
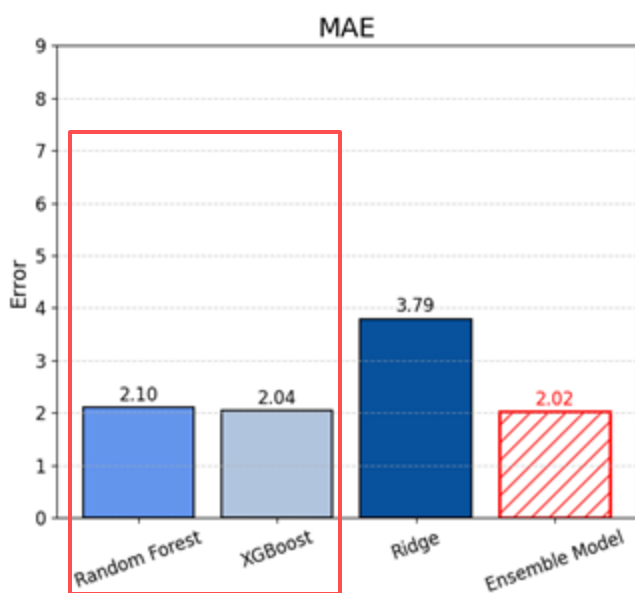
# 3. Methods

## g) Metrics

- Coefficient of Determination ( $R^2$ ) → Goodness of fit
- Mean Absolute Error (**MAE**) → Average error
- Root Mean Squared Error (**RMSE**) → Impact of large mistakes

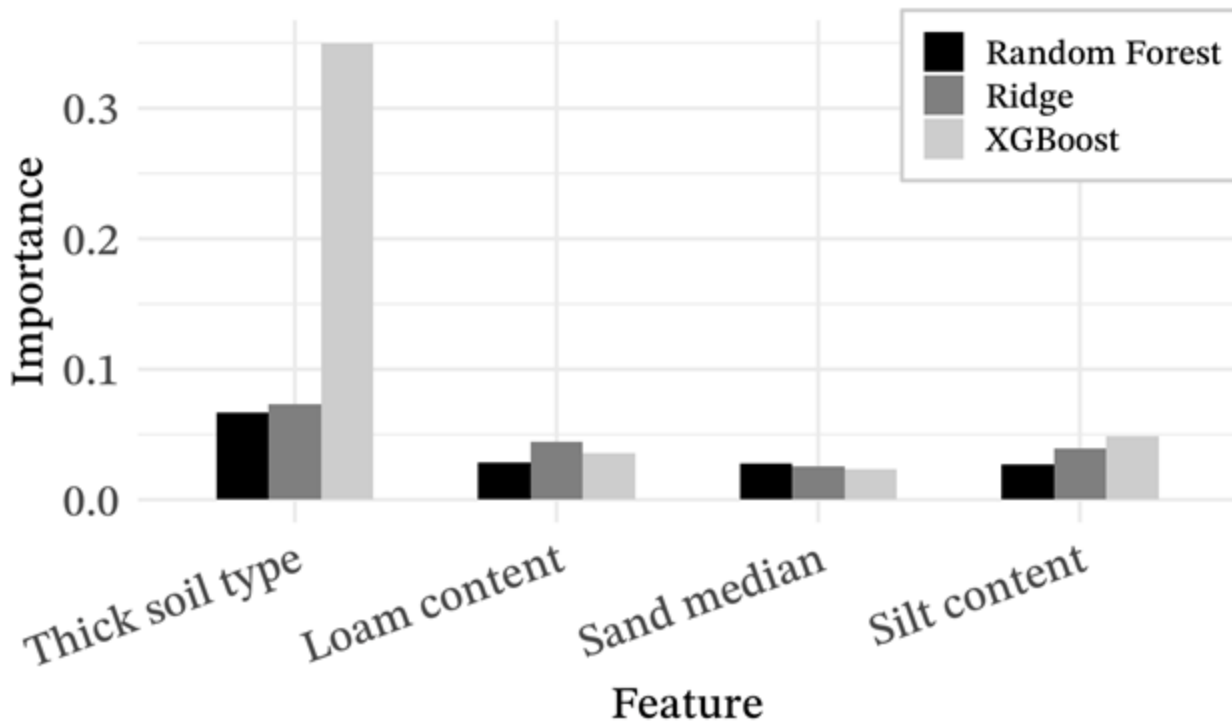
# 4. Results

## a) Performance evaluation



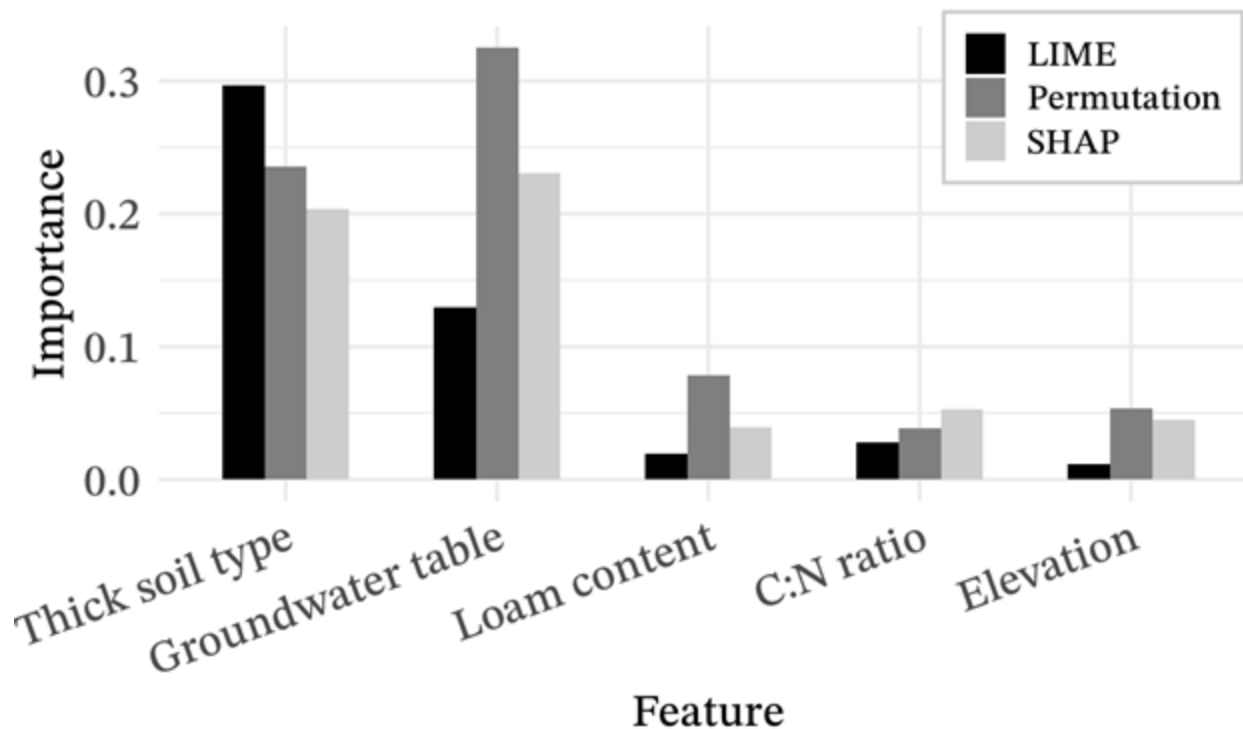
## 4. Results

### b) Feature Importances - Model Specific



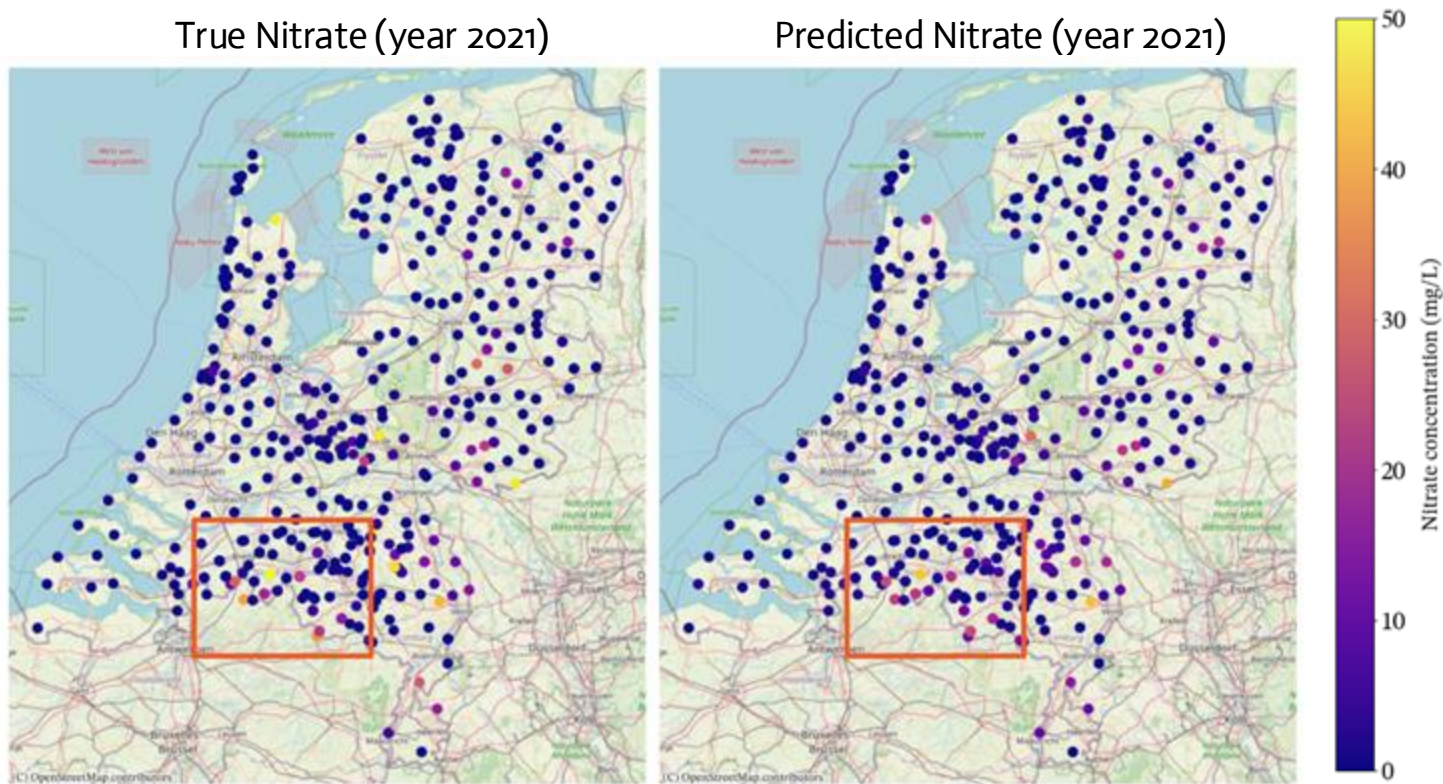
## 4. Results

### c) Feature Importances - Model Agnostic



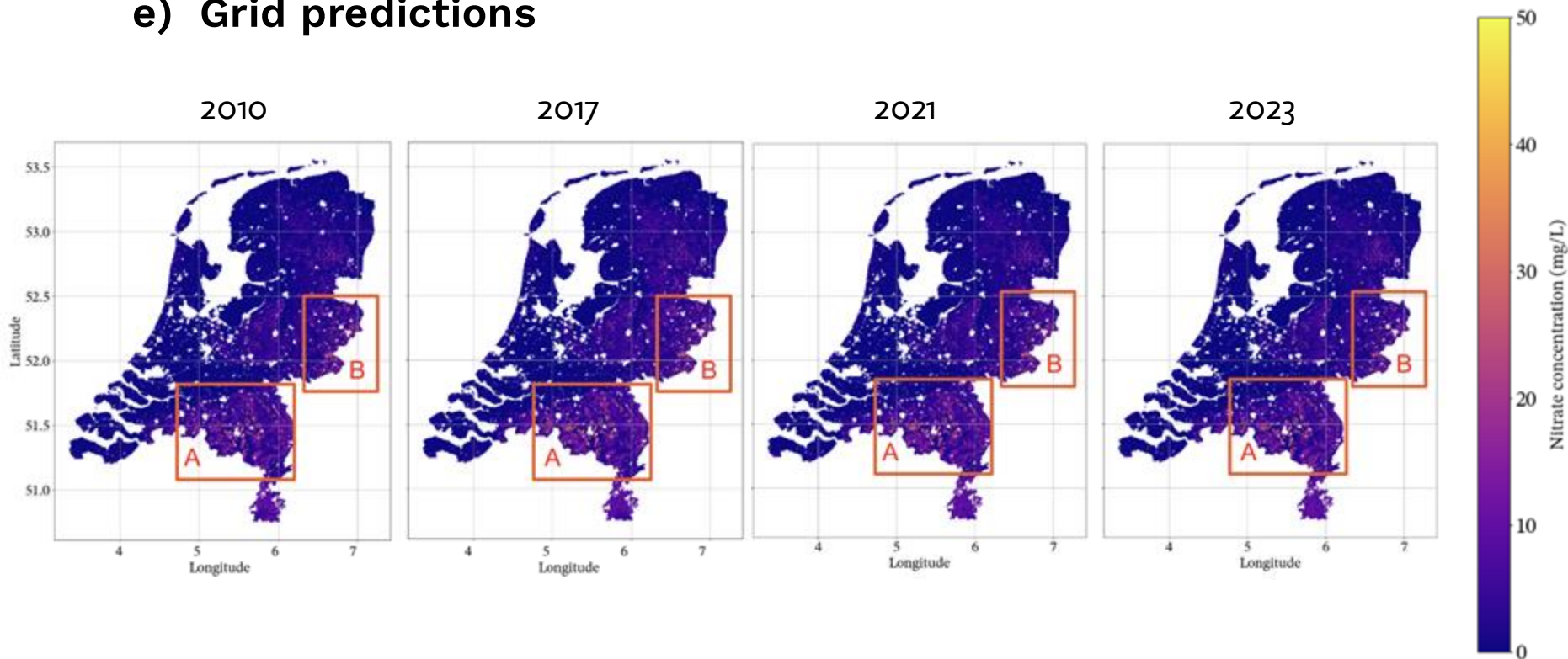
# 4. Results

## d) Test set predictions (year 2021)



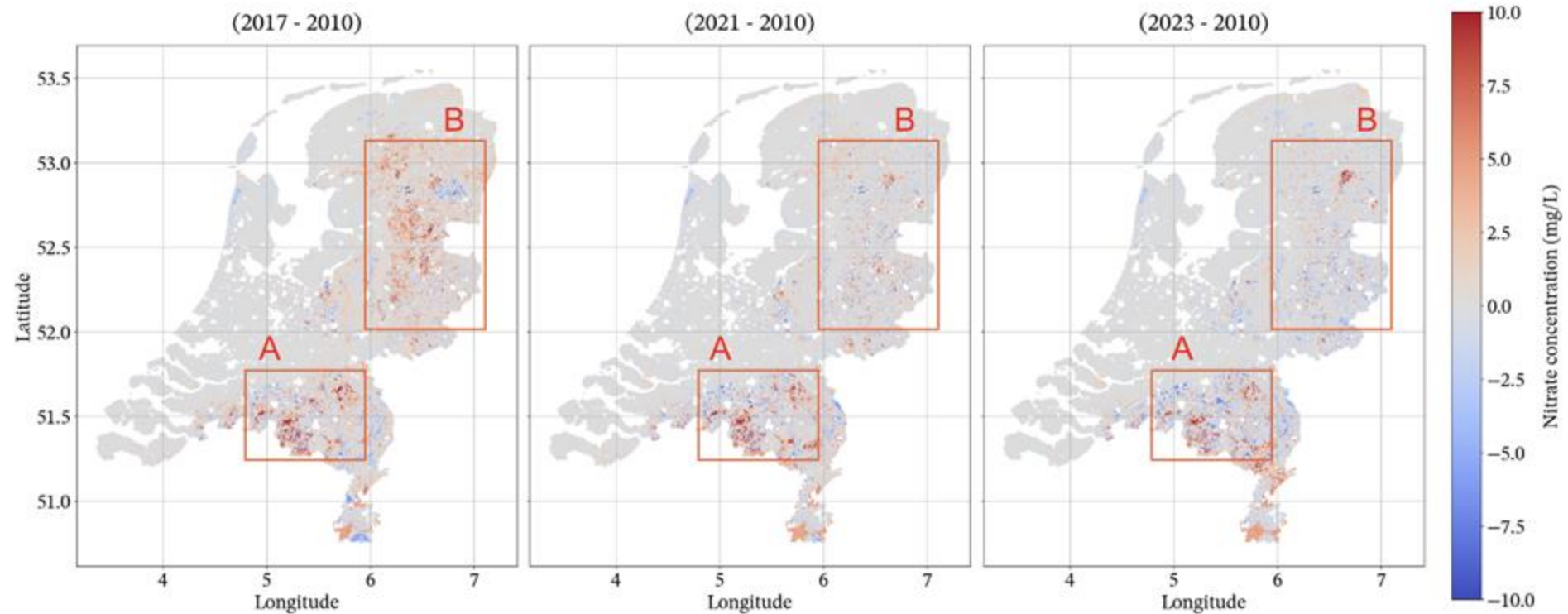
# 4. Results

## e) Grid predictions



# 4. Results

## f) Changes over years

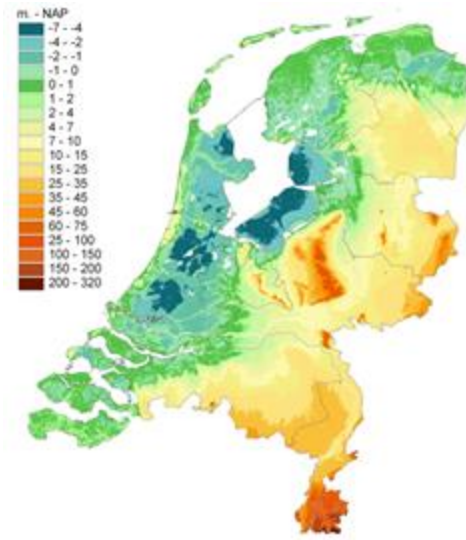




# 5. Discussion

## a) Feature importance insights

- Thick earth soils
  - Sandy, highly permeable
- Low loam content
  - Low values → unbalanced soil
- Deeper groundwater tables
  - Proxy for elevation



Elevation

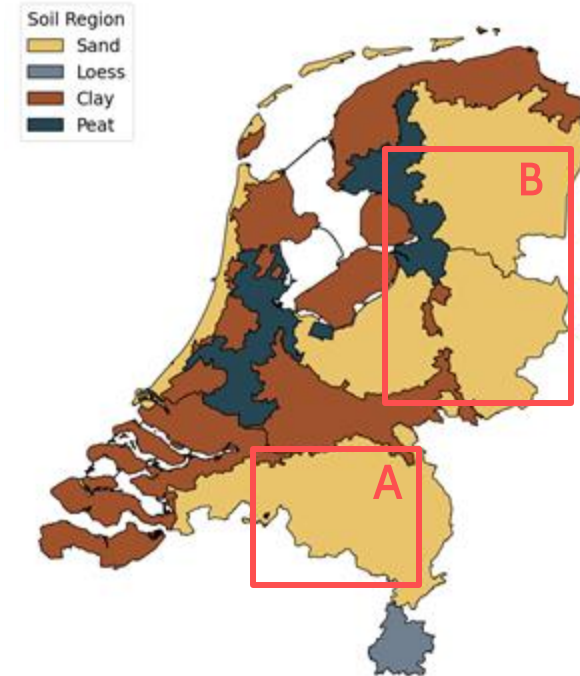


Soil type

# 5. Discussion

## b) Spatial trends

- High nitrate areas → nitrogen surplus after year 2015 [10]
  - Region A: dry, sandy soils, and low share of grasslands.
  - Region B: more grasslands, and higher proportion of peat.
- Anomaly: northern Drenthe (2023) → study limitation.



# 5. Discussion

## c) Limitations

- Spatial mismatch between groundwater & nitrate datasets ( $r \approx 0.6$ ).
- Models **underpredict nitrate values** above **6 mg/L** due to skewed nitrate dataset
- ~34 % of variance remains **unexplained** → Lack of fertilizer input data



## 6. Conclusion

- Random Forest and XGBoost outperformed Linear Regression
- Ensemble model performed best →  $R^2 = 0.66$
- Key predictors: thick soil types, loam content, and groundwater depth.
- Highest nitrate risk: South and North-East of the Netherlands.

### Future work:

- Add agricultural practice, and fertilizer data  
→ Capture finer-scale variability and improve predictions.

Thank you!

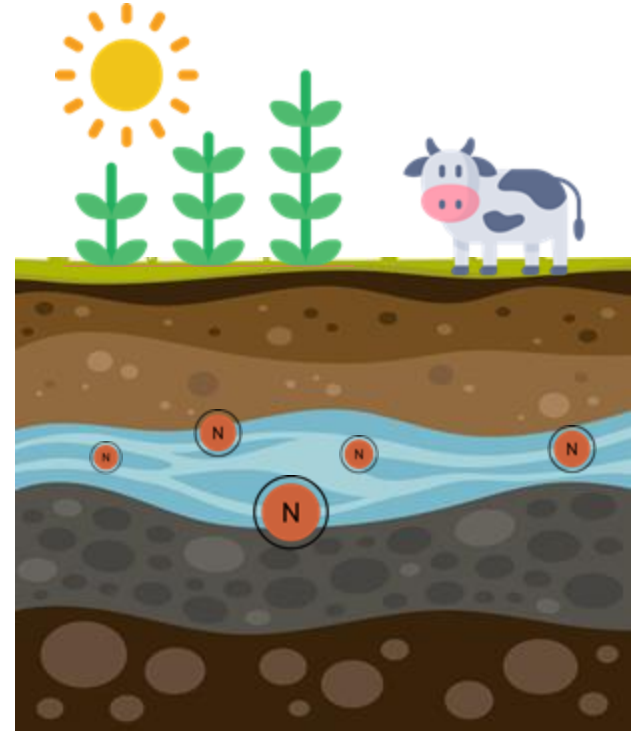


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- [j.d.cardenas.cartagena@rug.nl](mailto:j.d.cardenas.cartagena@rug.nl)



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