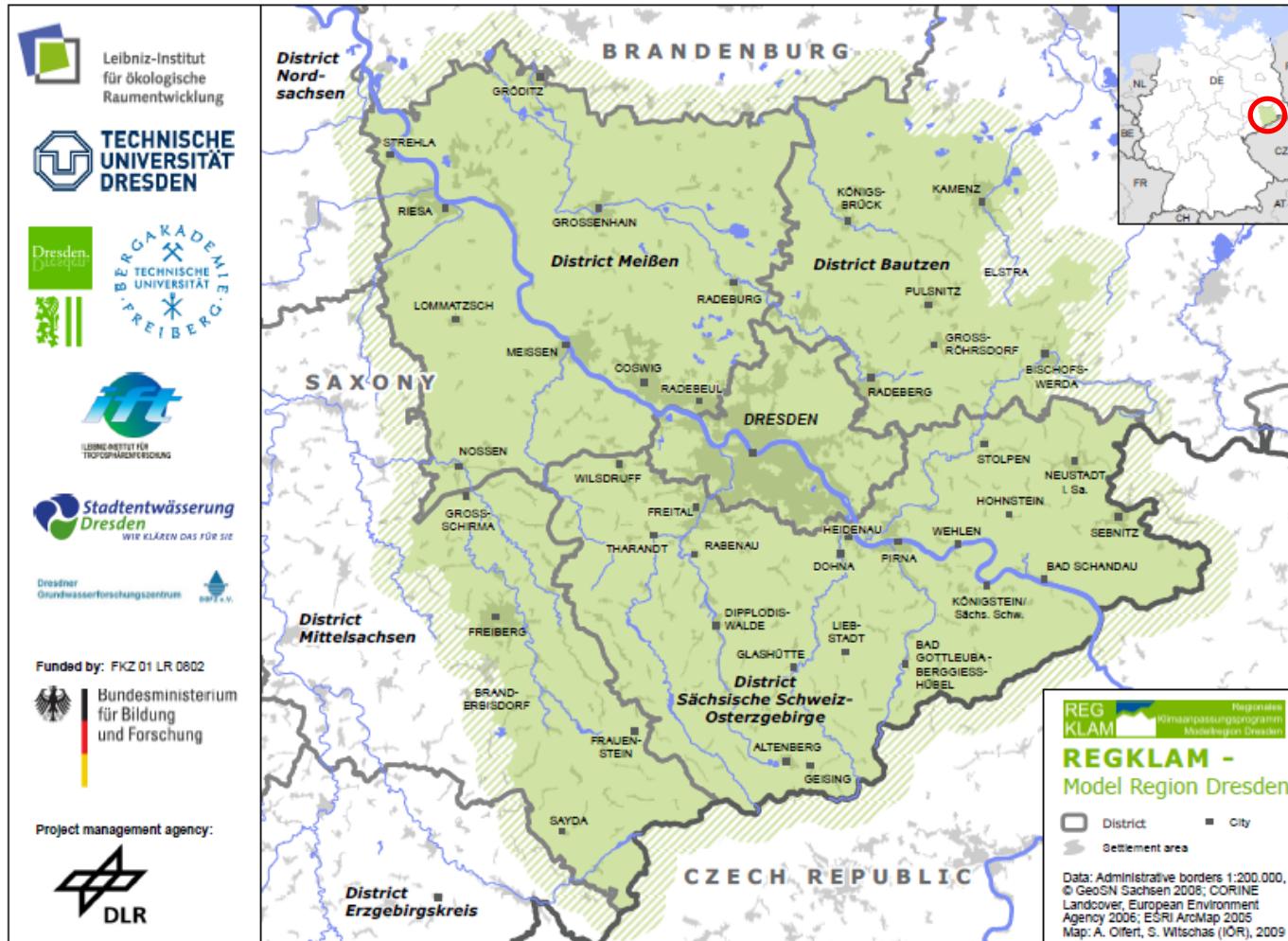


The impact of load estimation procedures on the simulation of nitrogen fluxes in a small mountainous watershed in Germany.

Stefan Julich,
Raphael Benning, Karl-Heinz Feger

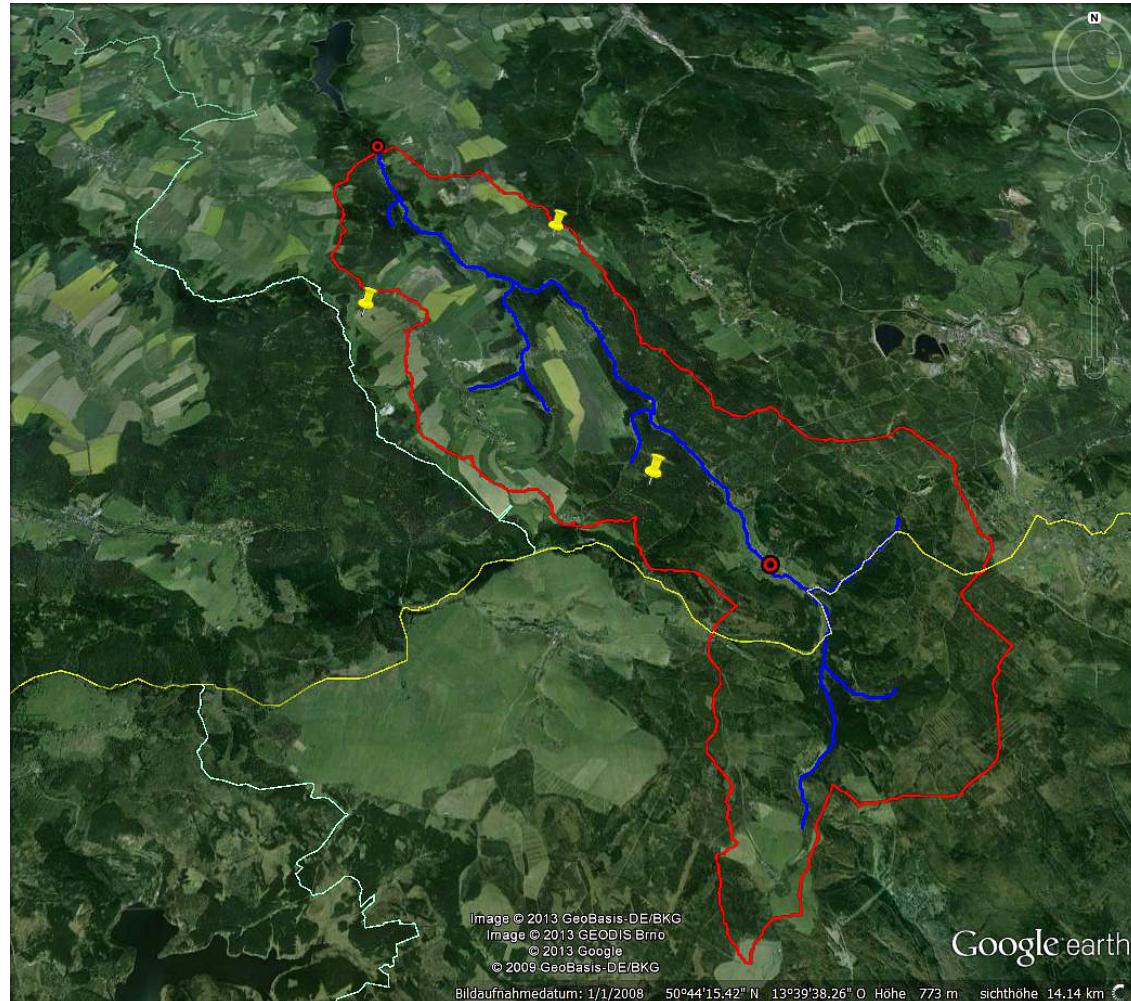
TU Dresden, Germany

Research area



Introduction

Research area - Ammelsdorf catchment



Climate

(period 1961 – 1990)

Precipitation

1096 mm a^{-1}

Mean annual temperature

$4,3 \text{ }^{\circ}\text{C}$

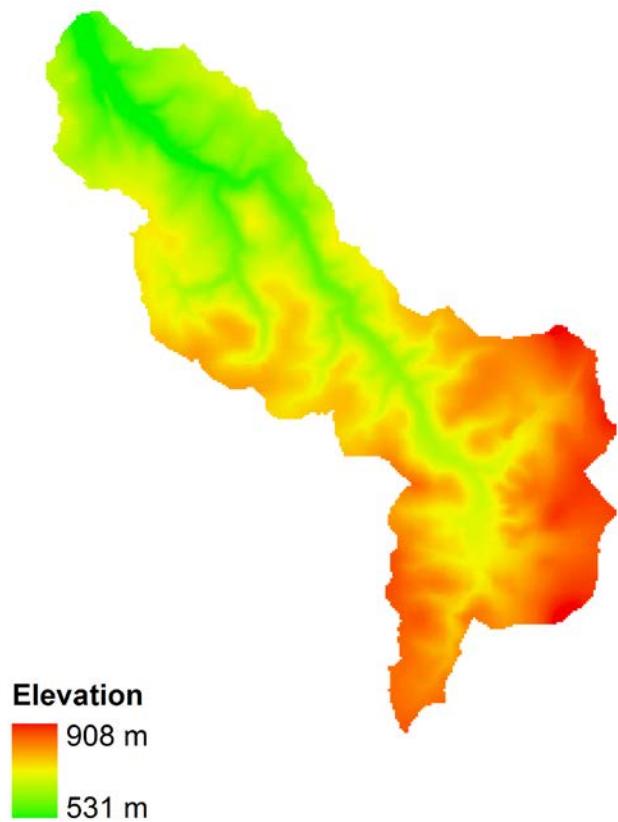
(Bernhofer et al., 2009)

Size

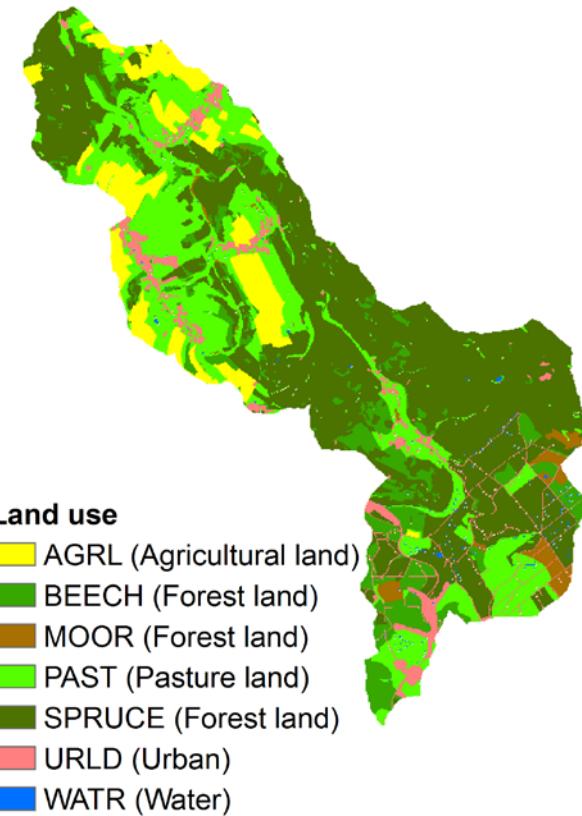
51 km^2

Introduction

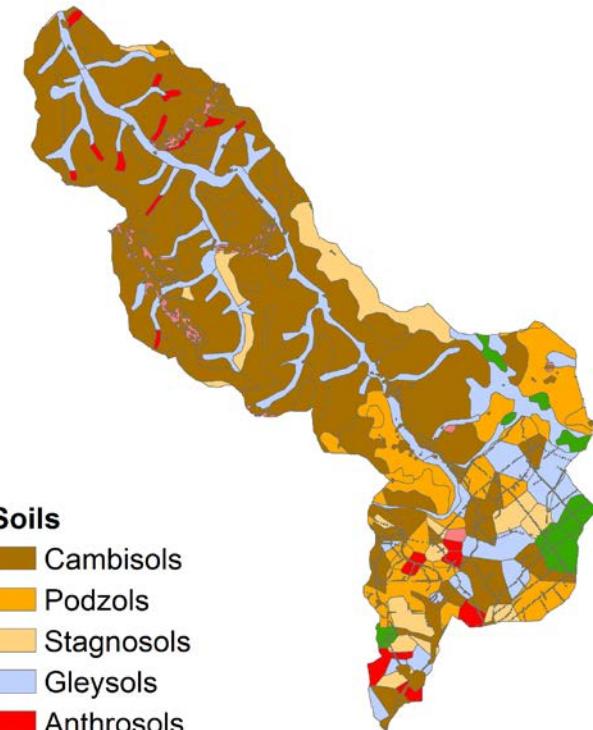
Input data for Ammelsdorf catchment



20 m resolution DEM
(GeoSN, 2010)

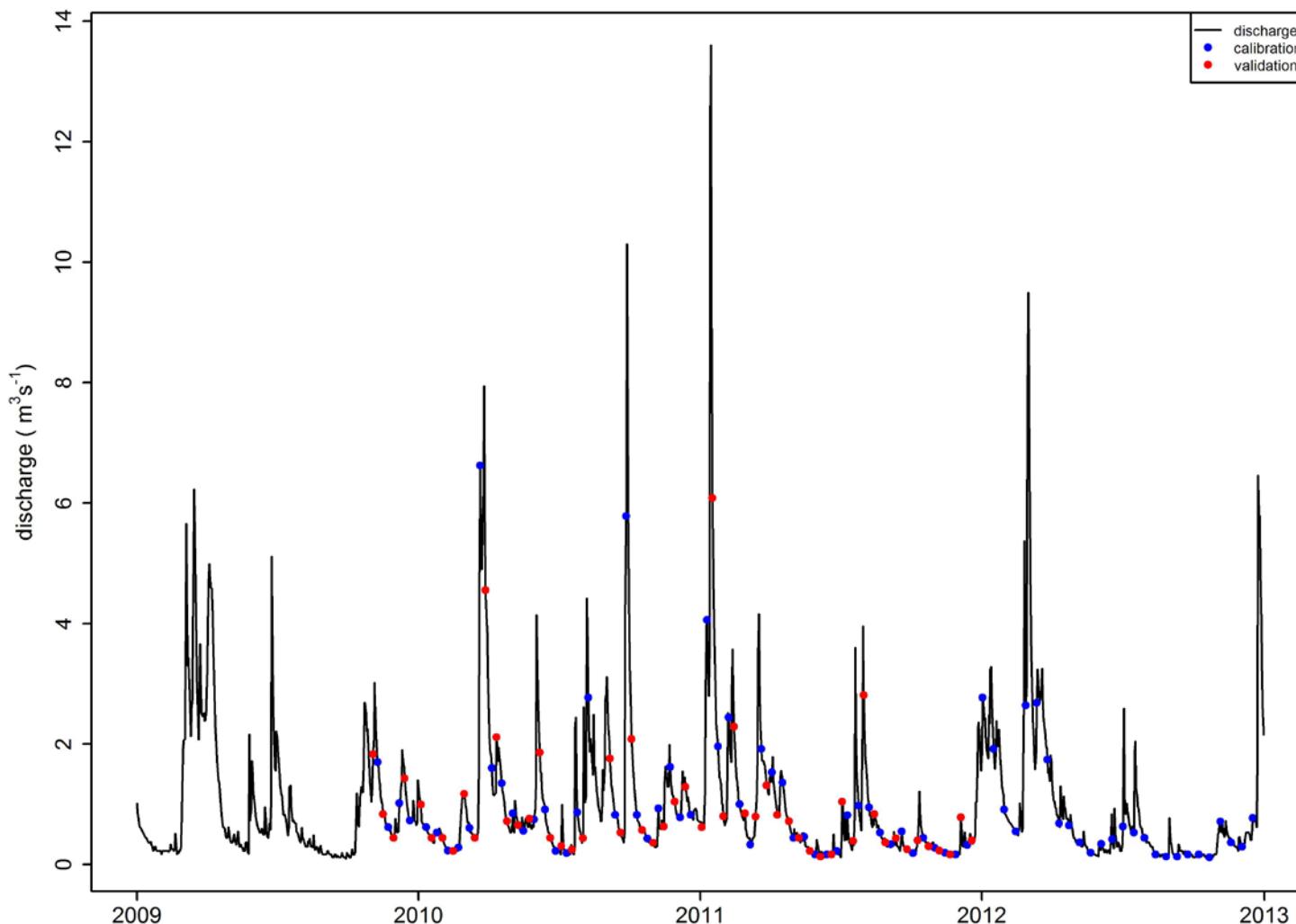


Land use, CIR 2005
(LfULG, 2010)



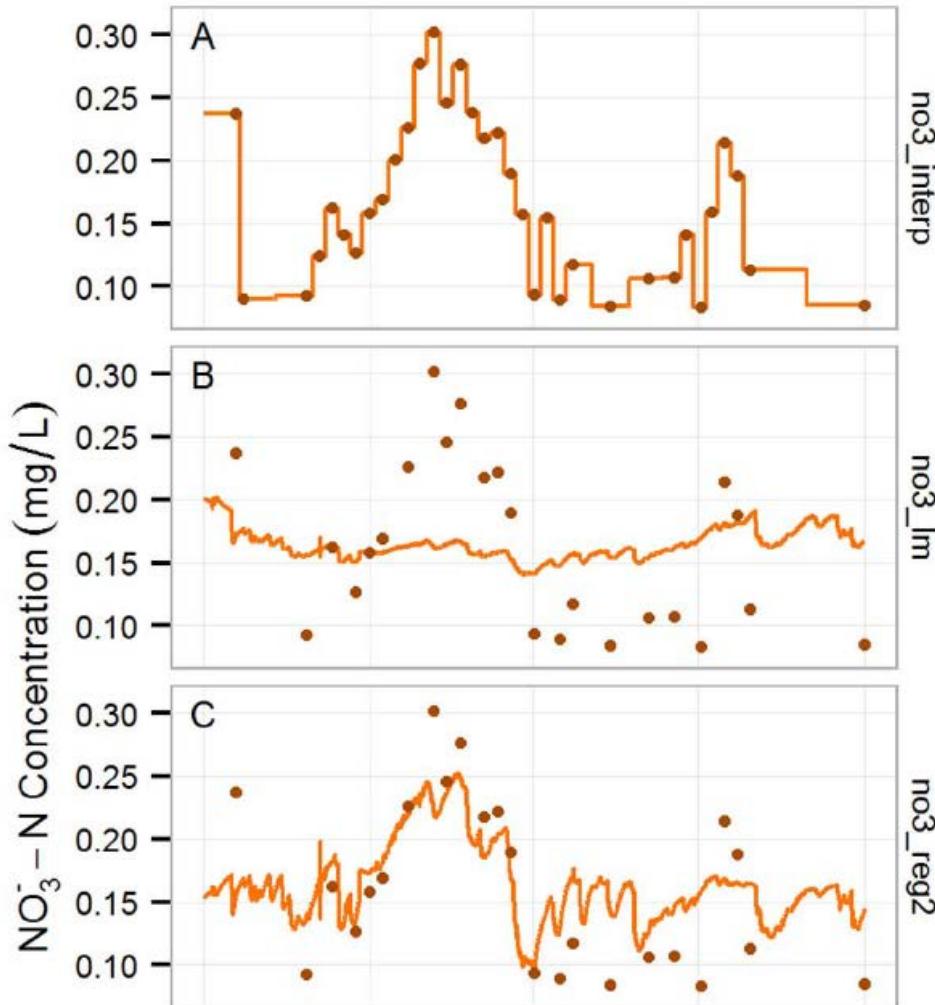
Soil map BK50
(LfULG, 2011)

Introduction



$\text{NO}_3\text{-N}$ [mg/l]
Min: 0.71
Max: 8.14
Mean: 1.85

The Loadflex-R Module



Relationship established via interpolation between measurements

Relationship established via linear model between measured discharge and solute concentration

Relationship established via linear regression model between measured discharge and solute concentration based on Loadest (Runkel et al. 2015)

Method

Linear Interpolation

Triangular Interpolation

Rectangular Interpolation

Spline Interpolation

Smooth Spline Interpolation

Distance Weighted Interpolation

Linear Regression Model

Loadest Regression Model 1

$$a_0 + a_1 \ln Q$$

Loadest Regression Model 2

$$a_0 + a_1 \ln Q + a_2 \ln Q^2$$

Loadest Regression Model 3

$$a_0 + a_1 \ln Q + a_2 dtme$$

Loadest Regression Model 4

$$a_0 + a_1 \ln Q + a_2 \sin(2\pi dtme) + a_3 \cos(2\pi dtme)$$

Loadest Regression Model 5

$$a_0 + a_1 \ln Q + a_2 \ln Q^2 + a_3 dtme$$

Loadest Regression Model 6

$$a_0 + a_1 \ln Q + a_2 \ln Q^2 + a_3 \sin(2\pi dtme) + a_4 \cos(2\pi dtme)$$

Loadest Regression Model 7

$$a_0 + a_1 \ln Q + a_2 \sin(2\pi dtme) + a_3 \cos(2\pi dtme) + a_4 dtme$$

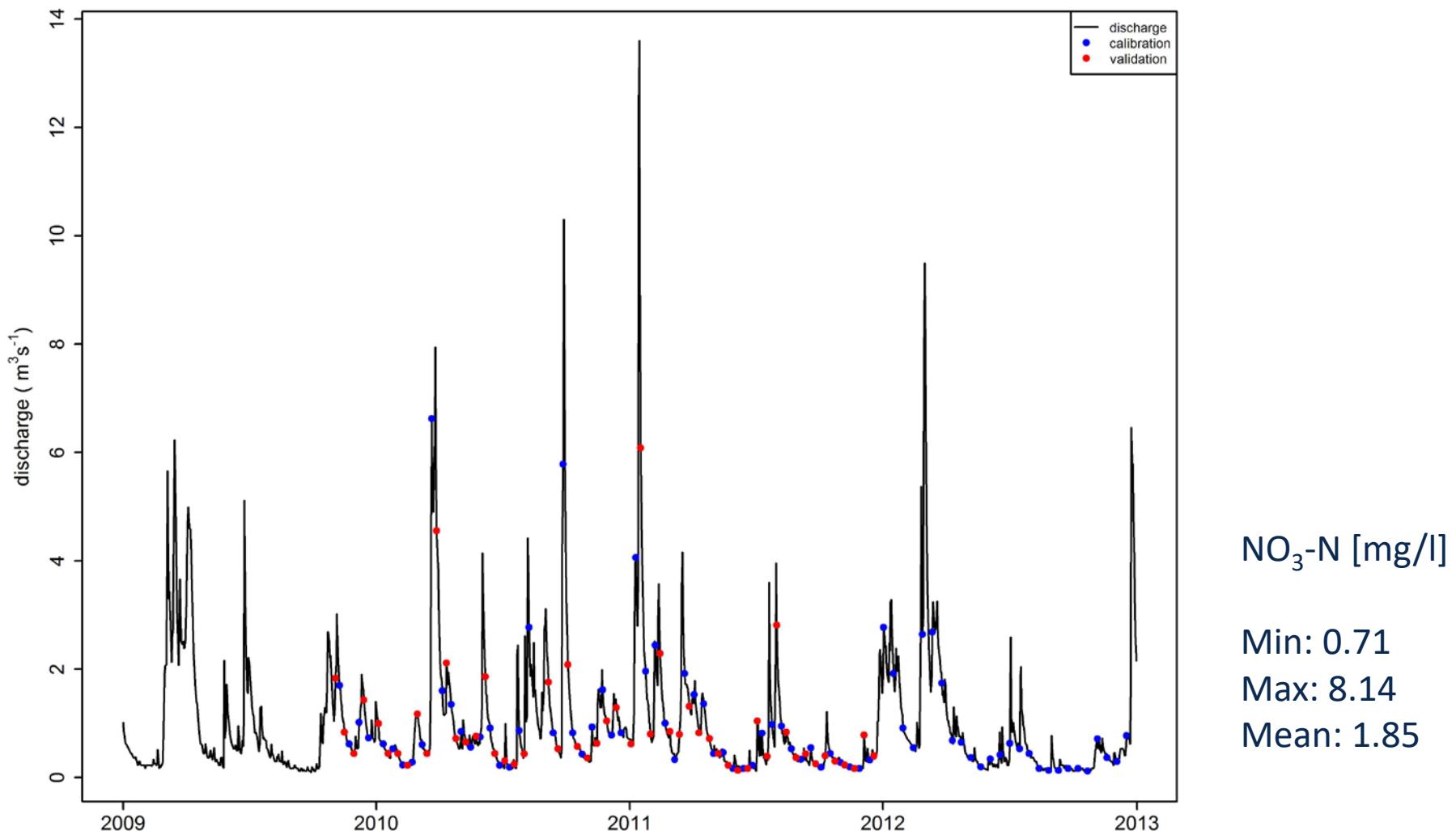
Loadest Regression Model 8

$$a_0 + a_1 \ln Q + a_2 \ln Q^2 + a_3 \sin(2\pi dtme) + a_4 \cos(2\pi dtme) + a_5 dtme$$

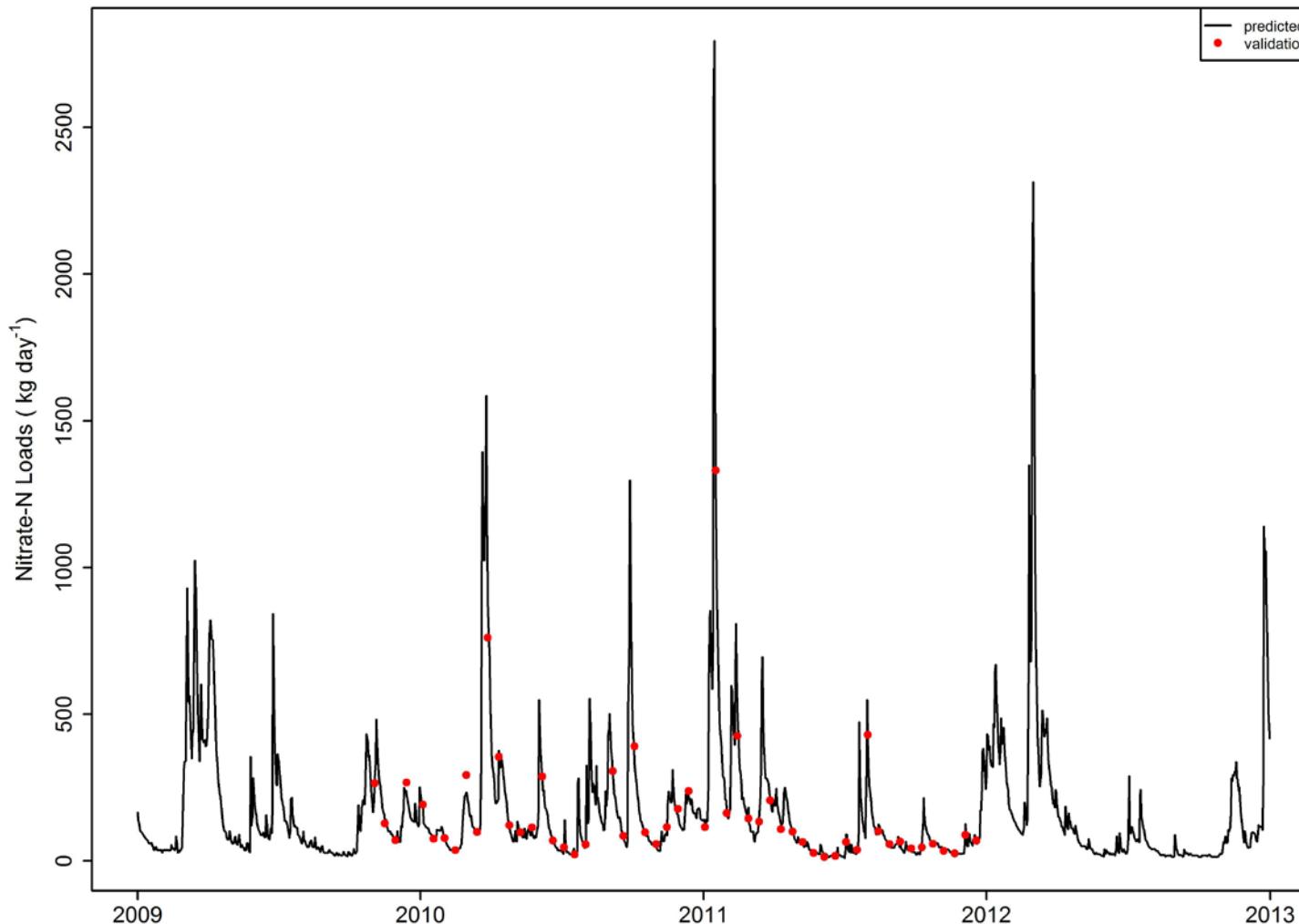
Loadest Regression Model 9

$$a_0 + a_1 \ln Q + a_2 \ln Q^2 + a_3 \sin(2\pi dtme) + a_4 \cos(2\pi dtme) + a_5 dtme + a_6 dtme^2$$

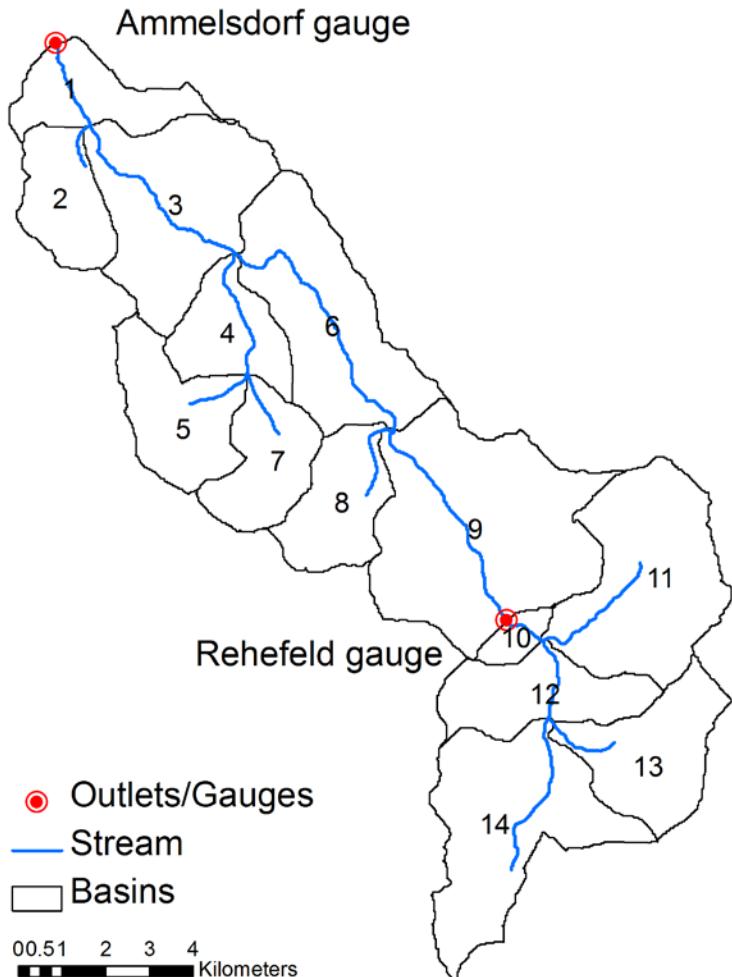
Loadflex Application



Loadflex Application



Model setup and measurement data



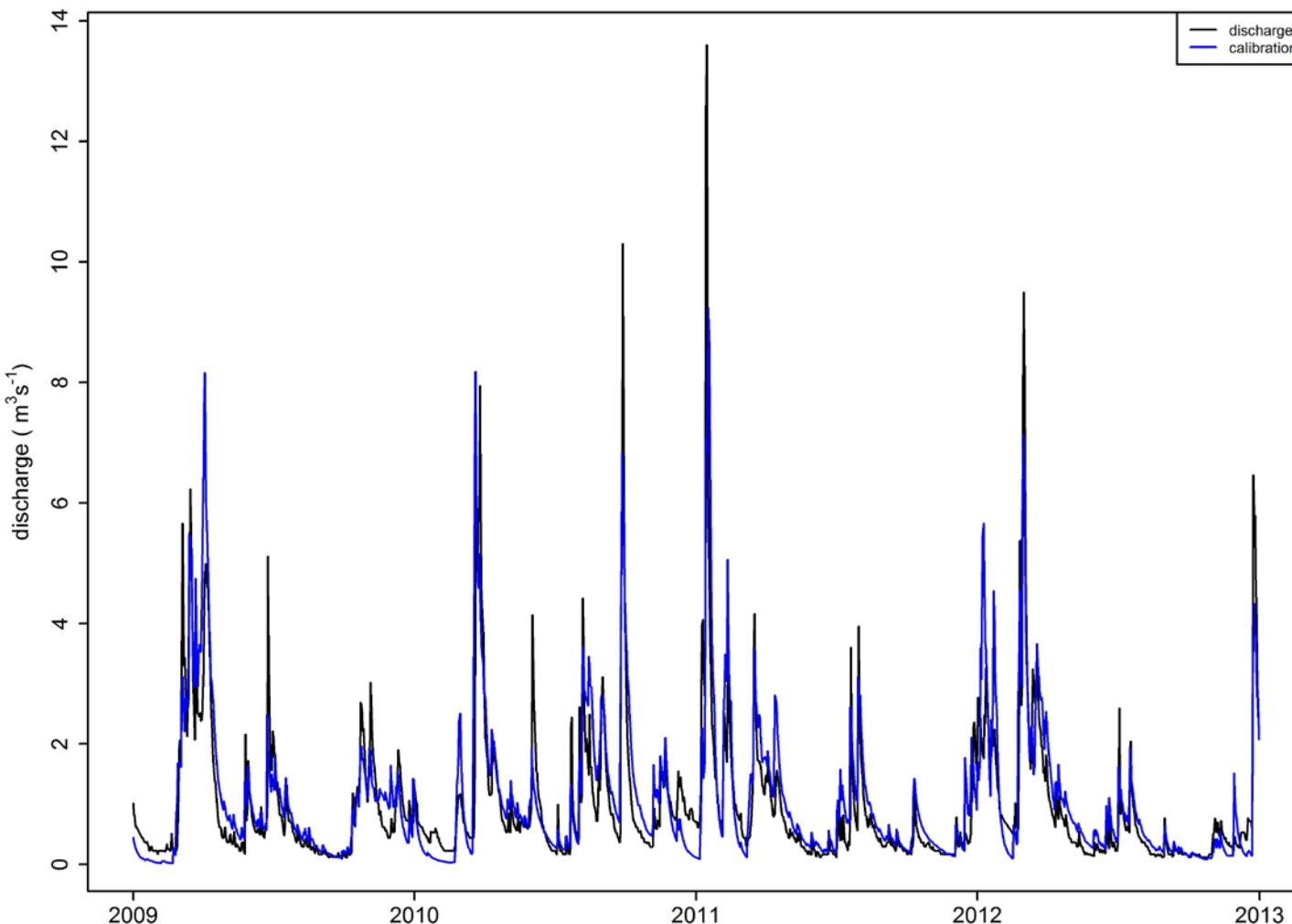
- 14 Subbasins
- 1312 HRUs
- Discharge data Ammelsdorf & Rehefeld (LHWZ, 2012)
2006-2012
- Water quality data Ammelsdorf (TUD)
2009-2012
- Fertilizer input ~230 kg N ha⁻¹a⁻¹

Calibration

Parameter	Min	Max	
SURLAG	0	3	Surface Runoff
SFTMP	-2	0.5	Snow
SMTMP	0	2	Snow
TIMP	0	1	Snow
CMN	0.0001	0.001	Nitrogen
NUPDIS	10	30	Nitrogen
NPERCO	0	1	Nitrogen
RSDCO	0.01	0.1	Nitrogen
CDN	0	2	Nitrogen
SDNCO	0.95	1.01	Nitrogen
AWC	-0.15	0.15	Soil
k_norock	-0.15	0.15	Soil
k_rock	0	200	Soil
CHN	0.01	0.3	Routing
CHK	0.01	30	Routing
ALPHA_BF	0.001	0.99	Groundwater
GW_DELAY	0	31	Groundwater
GW_REVAP	0.02	0.2	Groundwater
GW_QMN	0	100	Groundwater
DEPIMP	1500	3000	Groundwater

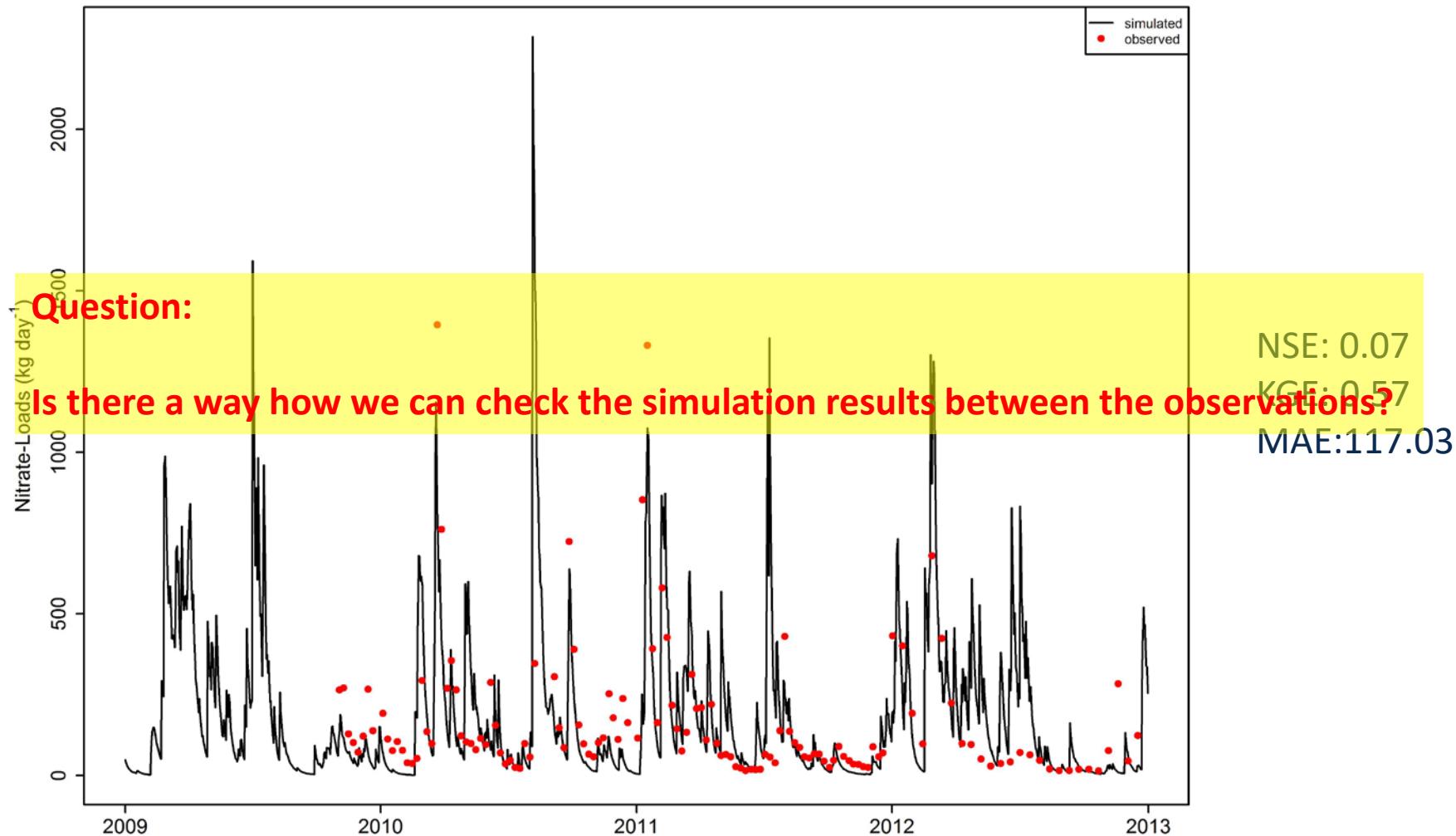
- 5000 parameter sets
- Latin-Hypercube-sampling with the FME R-package (Soetaert & Petzoldt, 2010) based on Pfannerstill et al. (2014)
- Best parameter selected according KGE

Results - Hydrology

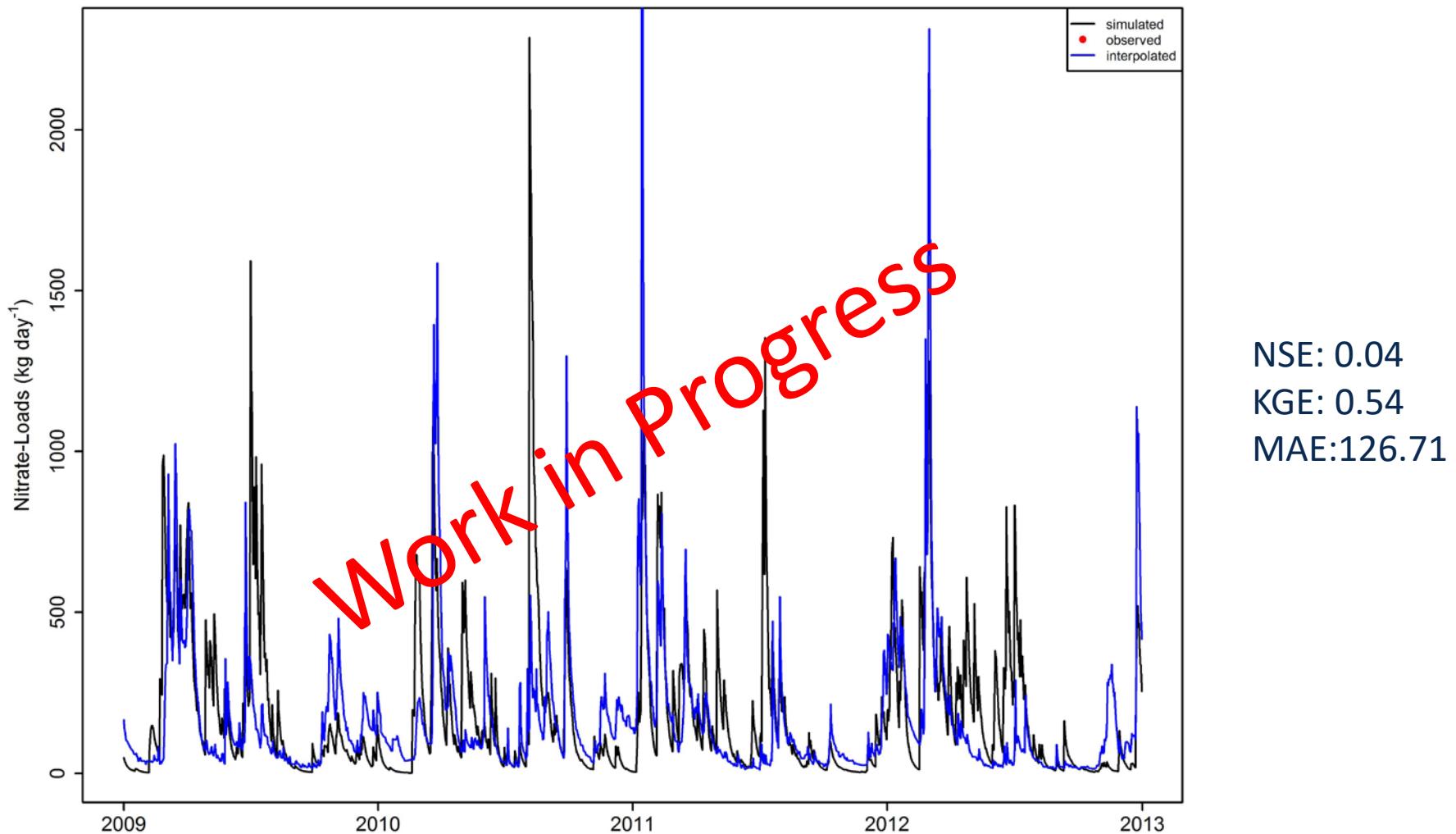


Objective Function:
NSE: 0.7
KGE: 0.82

Results – comparison simulated and observed loads



Results – comparison SWAT and Loadflex



Conclusions

- Discharge could be well captured by the model → weakness during snow melt periods
- Comparison of SWAT simulated Nitrate-Loads and observed Nitrate-Loads show larger uncertainties
- The comparison between the SWAT simulation and the Loadflex Predictions showed similar quality as for observations → but includes more data points
- Simulation reliable for times w/o observations?

Next steps:

- Include event based monitoring data in the Loadflex predictions → see whether this improves simulations quality

References

Appling, A.P.; Leon, M.C.; McDowell,W.H. Reducing bias and quantifying uncertainty in watershed flux estimates: The R package loadflex. *Ecosphere* **2015**, 6, 1–25.

Lorenz, D.; Runkel, R. *Rloadest: River Load Estimation*; U.S. Geological Survey: Mounds View, MN, USA, 2015.

Pfannerstill, M.; Guse, B.; Fohrer, N. (2014):Smart low flow signature metrics for an improved overall performance evaluation of hydrological models,
J. Hydrol., 510, 447-458, doi: <http://dx.doi.org/10.1016/j.jhydrol.2013.12.044>.

Soetaert, Karline and Petzoldt, Thomas, 2010: Inverse Modelling, Sensitivity and Monte Carlo Analysis in R Using Package FME. *Journal of Statistical Software*, 33(3), 1-28. DOI: 10.18637/jss.v033.i03



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