HUMAN AND ECOLOGICAL IMPACTS OF FRESHWATER DEGRADATION ON LARGE SCALES

Development and Integration of Spatial Models with Ecological Models for Spatial-ecological Analyses

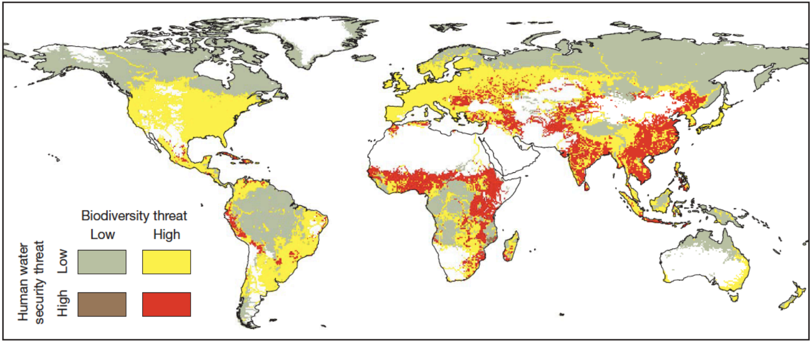
Avit Kumar Bhowmik

December 2, 2015

Ph.D. defense, Fachbereich 7: Natur- und Umweltwissenschaften

UNIVERSITÄT KOBLENZ · LANDAU

FRESHWATER ECOSYSTEMS ARE EXTENSIVELY DEGRADED ON LARGE SCALES



Vörösmarty et al., 2010. Nature

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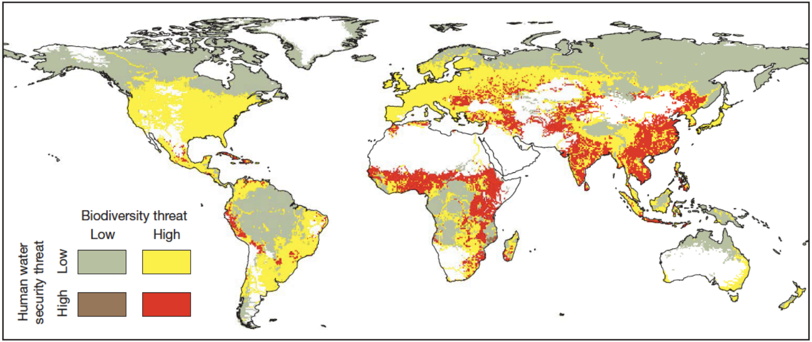

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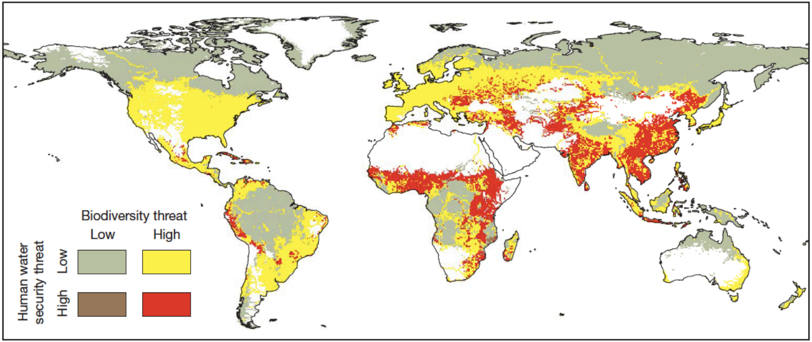

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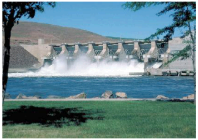
- 55% decline in 300 freshwater species (UNEP, 2015; WWF, 2015)
- significant decrease of discharge
  in 23% world's largest streams (Dai et al., 2009. J. Clim.)

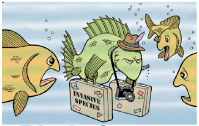
FRESHWATER DEGRADATION IS TRIGGERED BY FOUR GROUPS OF STRESSORS

Water pollution

Land use



Water resources development



Biotic factors

Vörösmarty et al., 2010. Nature; Dudgeon et al., 2005. Bio. Rev.

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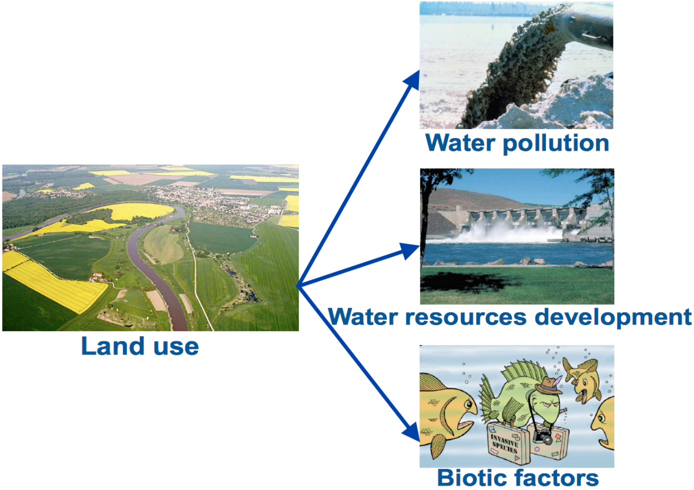

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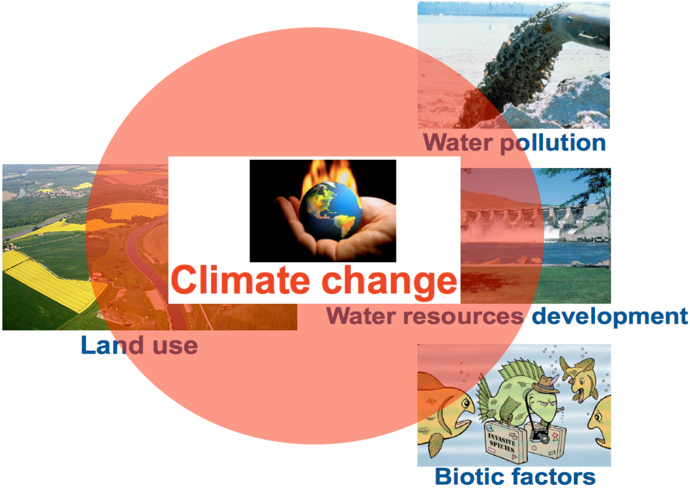

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RESPONSE:
POLITICAL FRAMEWORKS AIMS AT PRESERVATION AND RESTORATION

Developed countries

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Water Framework Directive

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LARGE SCALE APPROACHES CAN COMPLEMENT SMALL SCALE APPROACHES

- Local and regional species richness often exhibit positive relationships (Heino et al., 2013. Fresh. Bio.; Hugueny et al., 2010. Am. Fish. Soc. Symp.)

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- Integrated and transboundary freshwater management (EC, 2010)
- Data-gap filling by novel methods and available secondary datasets (Hengl, 2009. Geostat. Map.; Törnqvist et al., 2011. Env.Int.)

SPATIAL MODELS ARE INDISPENSABLE TOOLS FOR LARGE SCALE ECOLOGICAL ANALYSES

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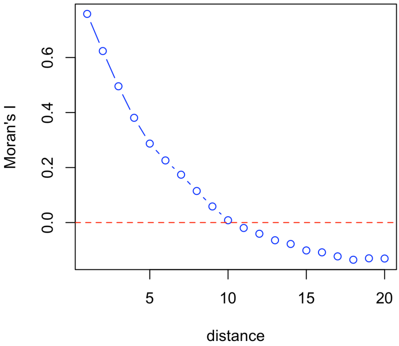

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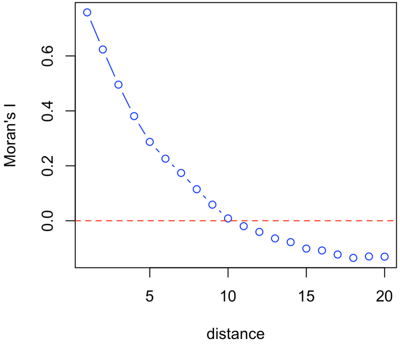

MY PH.D. THESIS ENVELOPS FOUR STUDIES
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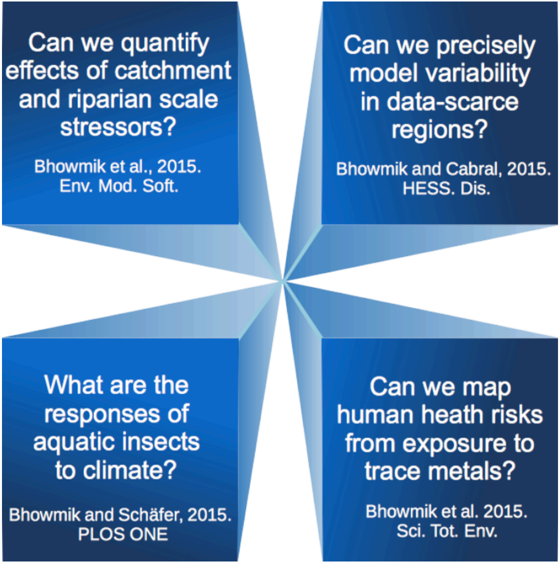
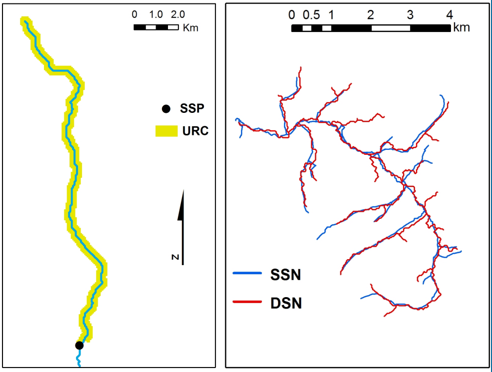


Quantifying catchment and riparian scale stressors



Bhowmik et al., 2015. Env. Mod. Soft., 63: 240-250

AUTOMATED ACCUMULATION THRESHOLD SELECTION AND RIPARIAN CORRIDOR DELINEATION (ATRIC)

Data

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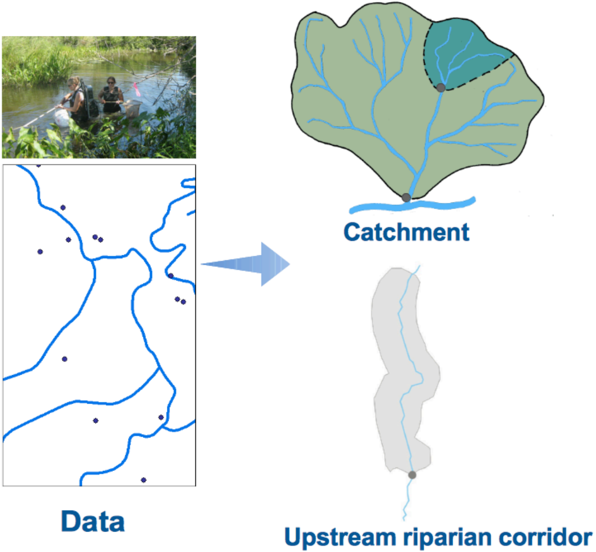

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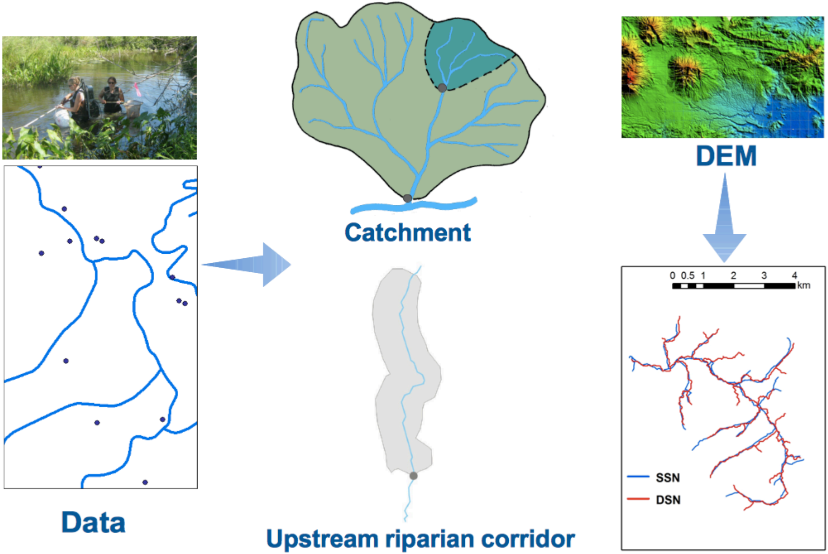

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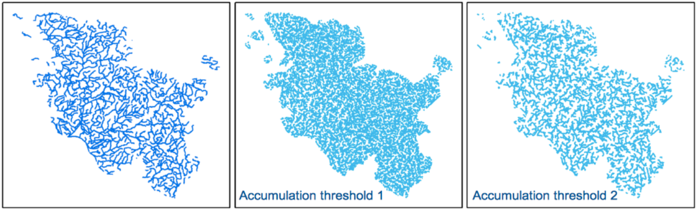

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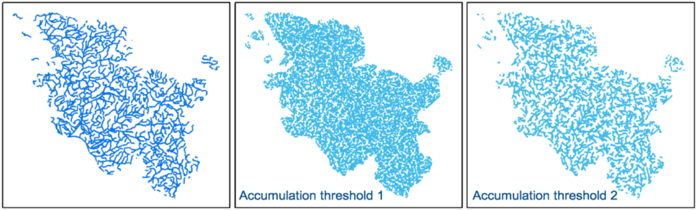

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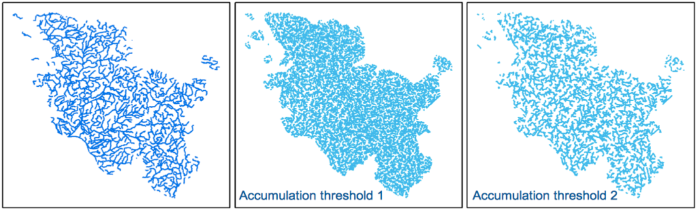

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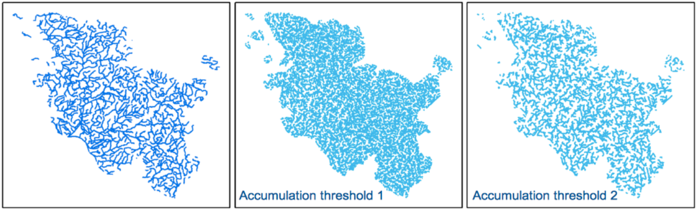

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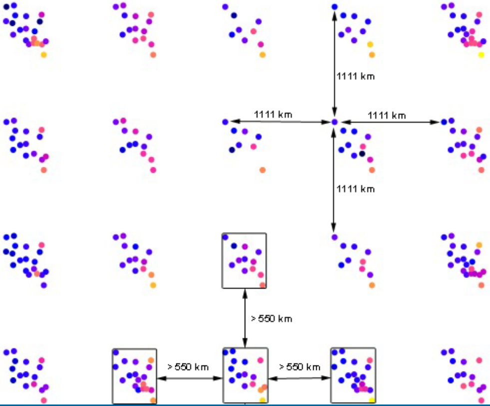
- Available algorithms: (i) for small scale data (ii) inaccessible

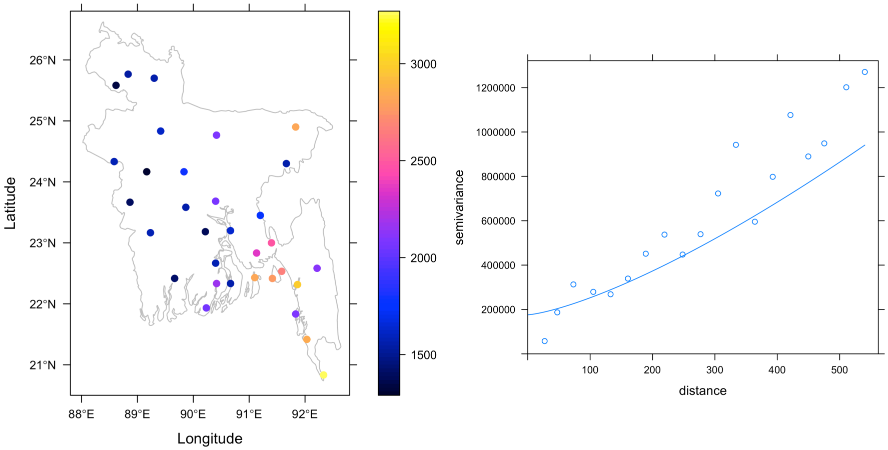
(Lin et al., 2006. Hydrol. Process.; Heine et al., 2004. Ann. Assoc. Am. Geogr.)

Modelling spatial variability with precision



Bhowmik and Cabral, 2015. HydroESS. Dis., 12: 2243-2265

SPATIALLY SHIFTING TEMPORAL POINTS (SSTP)



Webster and Oliver, 2007. Geostat. Env. Sci.

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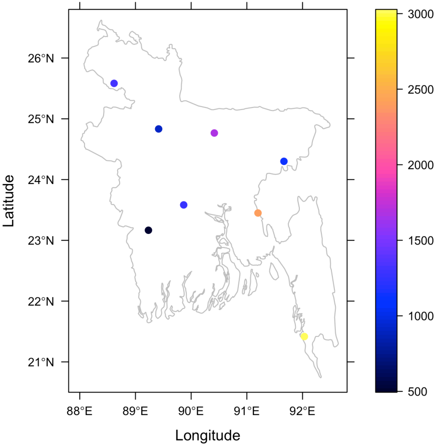

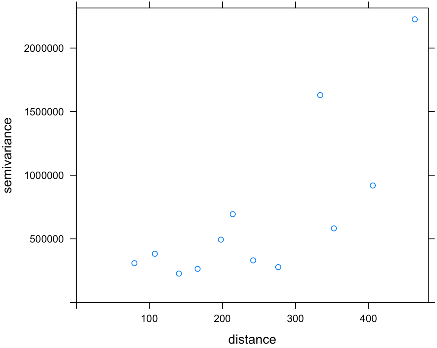

Oliver, 2010. Var. Krig.; Truong et al., 2012. Comp. Geosci.

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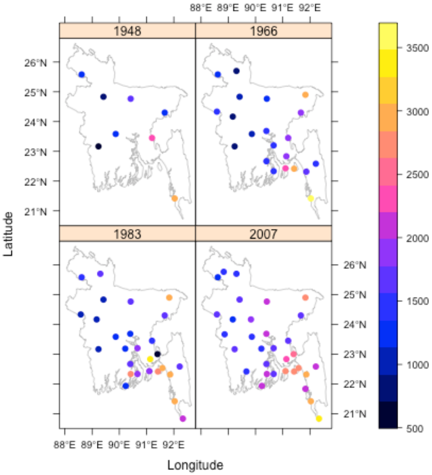

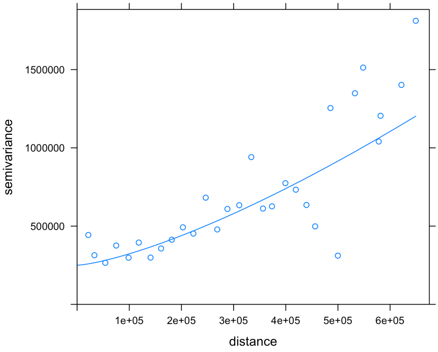

Wagner et al., 2012. J. Hydrol.

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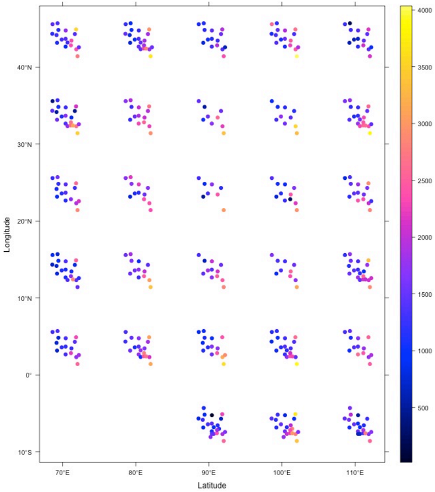
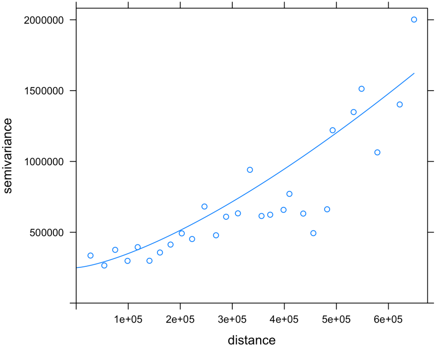
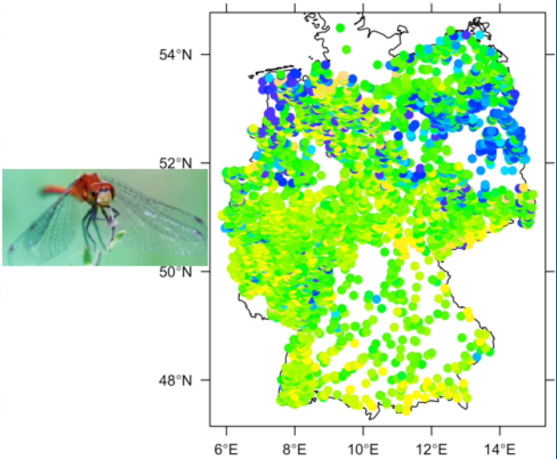




Climate response of aquatic insects



Bhowmik and Schäfer, 2015. PLOS ONE. e0130025

CLIMATE IS THE PREDOMINENT DRIVER OF FRESHWATER ASSEMBLAGES ON LARGE SCALES

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Biological and ecological traits were associated with climate change

(Hershkovitz et al., 2015. Eco. Ind.; Conti et al. 2013. Hydrobio.)

OUR RESEARCH QUESTIONS WERE TWO-FOLD

1. which climate-associated traits and organism groups show the highest potential for changing distribution pattern?

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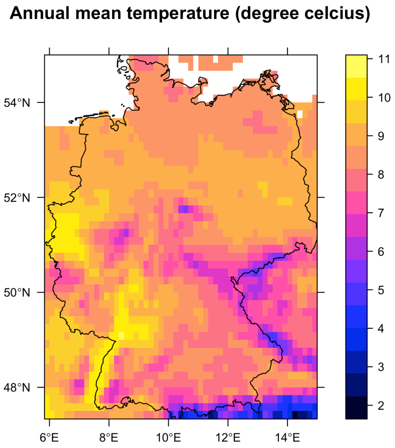
2. which are most influential climatic aspects for traits and organism groups showing highest potential for changing distribution?

BIOMONITORING DATA FROM 4,752 STREAM SITES AND 35 GLOBAL BIOCLIMATIC INDICES

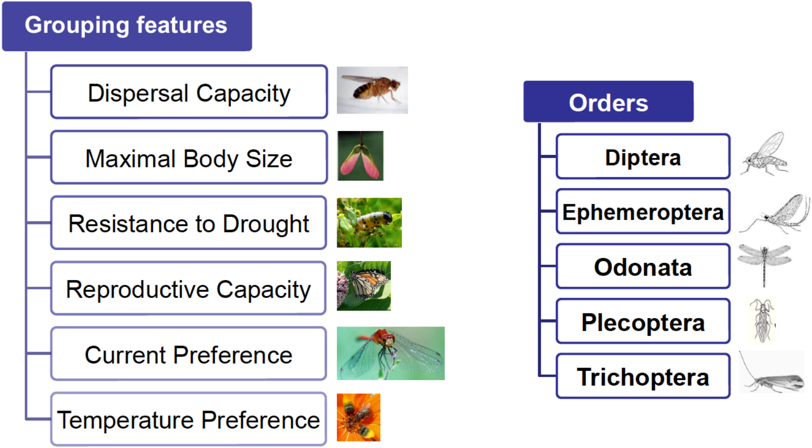


357,000 km^2

18 km

Biss et al., 2006; Kriticos et al., 2012. Met. Eco. Evo.

CLIMATE-ASSOCIATED TRAITS
FROM 6 GROUPING FEATURES AND 5 AQUATIC INSECT ORDERS



Trait databases: freshwater ecology (Schmidt-Kloiber and Hering, 2015), Tachet (Usseglio-Polatera et al. 2000)

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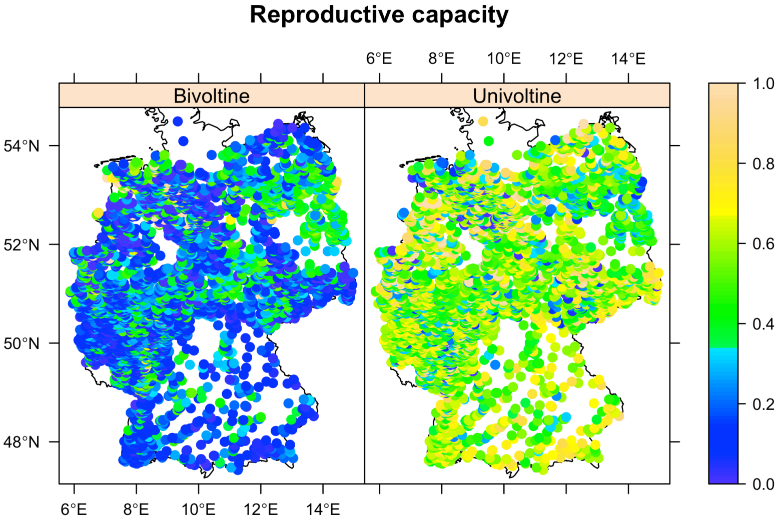

Schmera et al. 2014. Fresh. Bio.

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4. Relationship between abundance-weighted traits and individual bioclimatic indices

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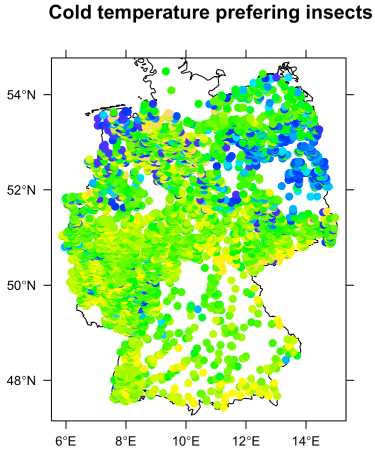

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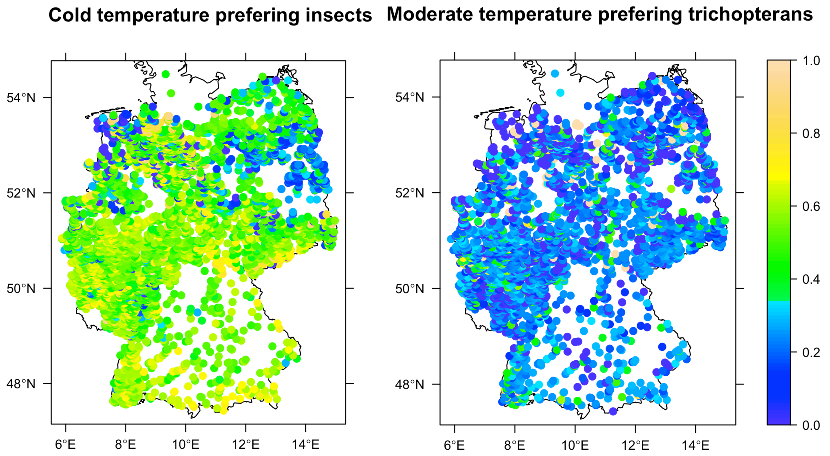

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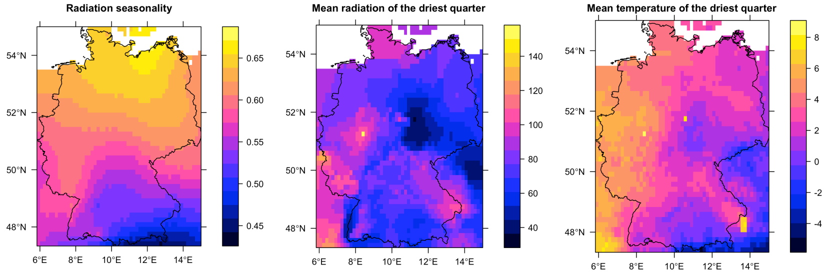

WE ANTICIPATE CHANGE IN AQUATIC INSECT DISTRIBUTION PATTERN ALONG THE LONGITUDINAL GRADIENT IN GERMANY

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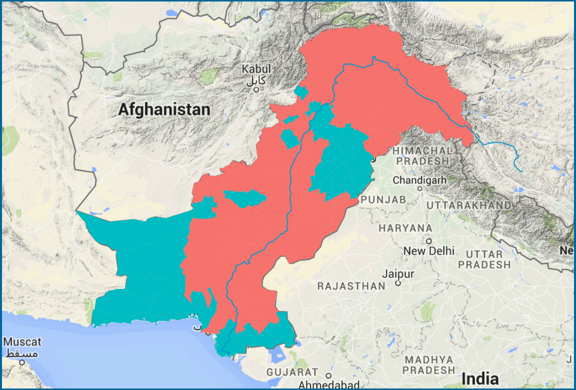
- Moderate temperature preferring trichopterans mostly occur in the North may extend their range (Hering et al. 2009. Aq. Sci.)

ADAPTATION MAY OCCUR AND AGGLOMERATE ECOLOGICAL EFFECTS

- Trait evolution (Lancaster and Downes, 2010. Riv. Res. App.)
- Trait adaptation Zeuss et al., 2014. Nat. Com.

Human health risks from trace metals



Bhowmik et al. 2015. Sci. Tot. Env. 538: 306-316

1/3 OF ANNUAL MORTALITY IN PAKISTAN IS ATTRIBUTED TO CONTAMINATED DRINKING WATER

Azizullah et al. 2011. Env. Int.

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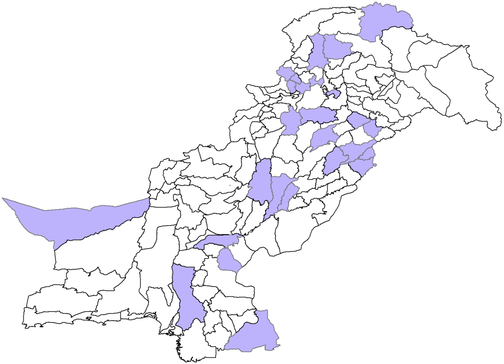

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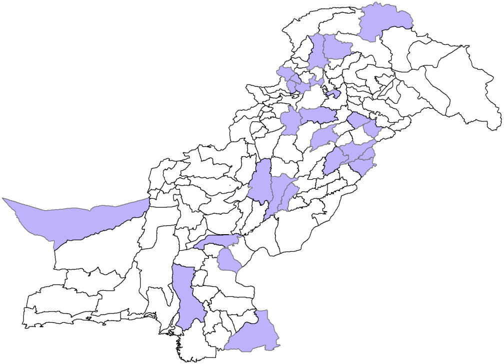

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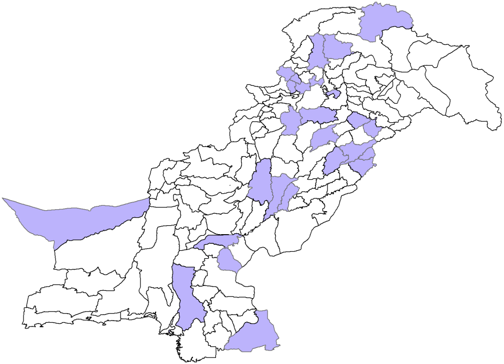

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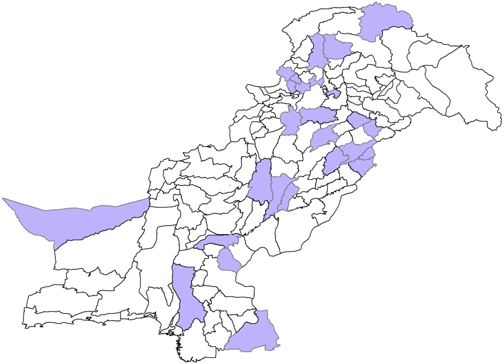

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Low global representativeness, GCV ≥ 1, non-stationarity

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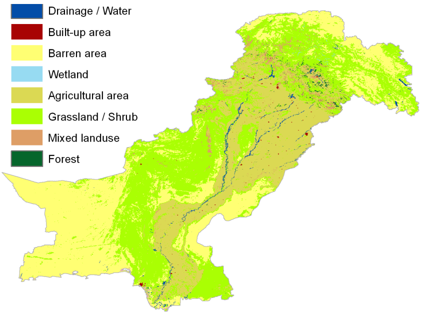

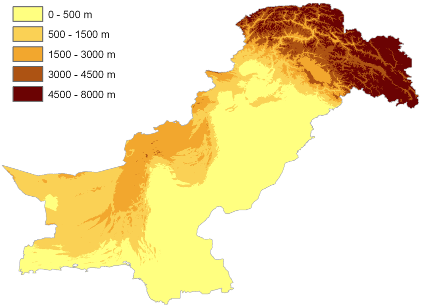

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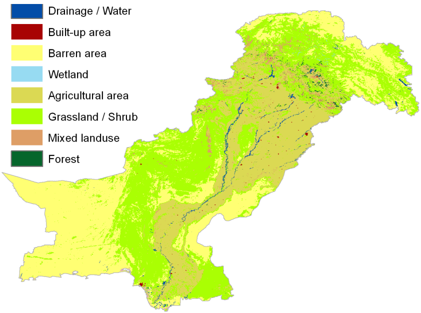

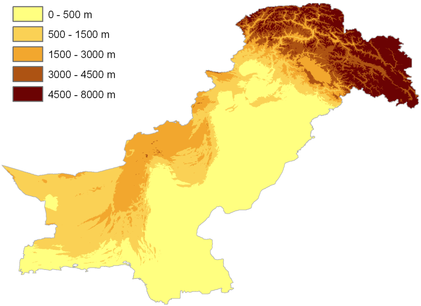

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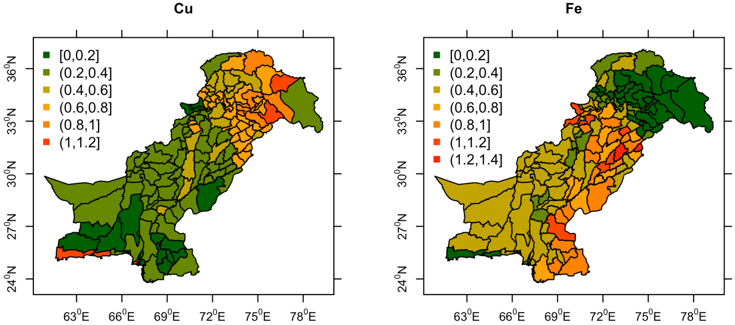
Global soil properties (Batjes, 2000. ISRIC) SOC, SCC, WC, pH

WE ESTIMATED AREA AND POPULATION AT RISK BY COMPARING TO "WHO" GUIDELINE THRESHOLDS



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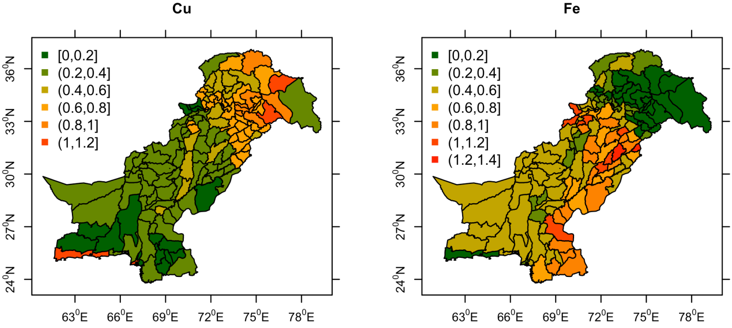

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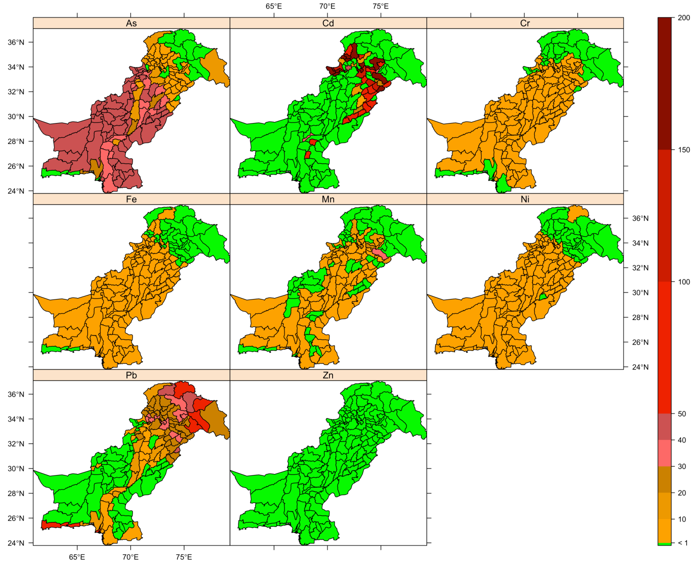
$$RQ_{T,z} = \frac{\hat{C}_{z,0}}{C_{WHO-T}}$$

RQ>1 at risk $RQ \leq 1$ negligible risk (WHO, 2011)

MORE THAN 53 % OF TOTAL AREA AND 74 MILLION PEOPLE ARE AT RISK FROM ARSENIC, CHROMIUM, IRON, NICKEL AND LEAD



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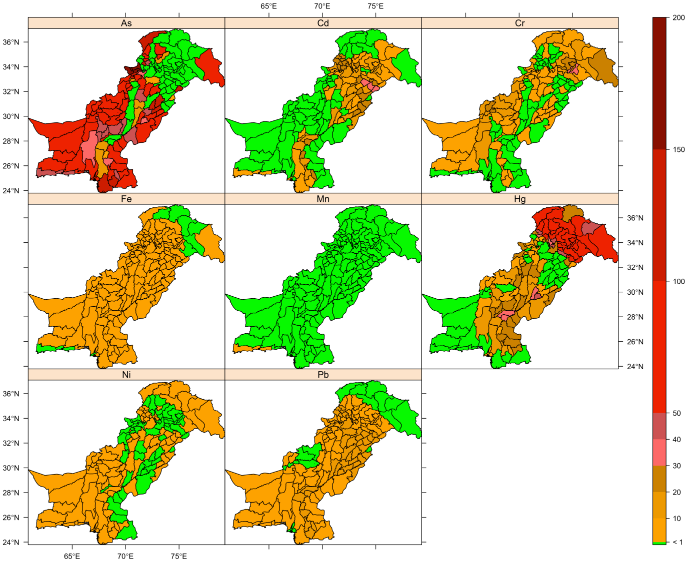

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- SDZ ≥ 0.7 except for cadmium and zinc in ground water, and cadmium and manganese in surface water
- Calibrated spatial predictors are in agreement with the causes of trace metal contamination e.g. As_SW~SOC + pH
  (Husain et al. 2012. Int. J. Ecol. Env. Geol.)

THE PREDICTIONS INFORM WATER RESOURCES MANAGEMENT ON POTENTIAL HOT SPOTS

- Predictions may not reflect true trace metal concentration variation 453 km $\leq$ kernel bandwidth $\leq$ 1335 km

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- May also indicate indirect effects e.g. via consumption of vegetables irrigated with contaminated water (Amin et al., 2012. ASSET)

FRESHWATER DEGRADATION IS ALARMING

SCIENCE CAN ACT PRO

FUTURE RESEARCH CHALLENGES

- Trait convergence, Aquatic - terrestrial interaction and Trait potential to distinguish between stressors
- Filling data gaps: Crowd-sourced data

Thank You

Jun. Prof. Dr. Ralf B. Schäfer

Dr. Markus Metz

Dr. S. A. M. A. S. Eqani

The open-source and
R community

Universität Koblenz · Landau