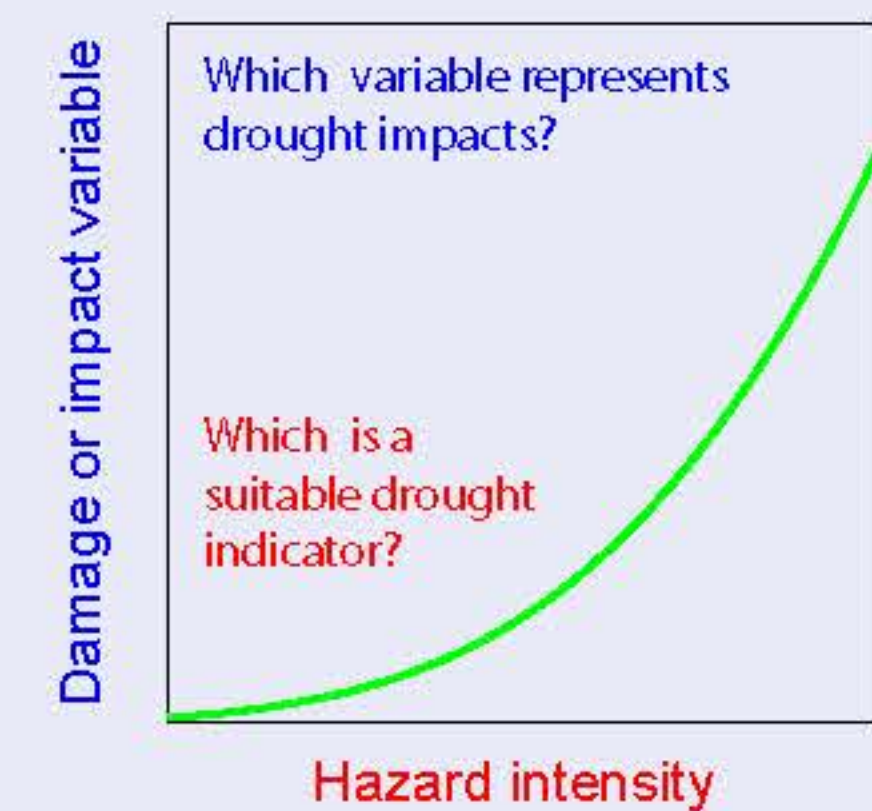


Motivation and aim

In natural hazard analysis, damage functions relate hazard intensity to the negative effects of the hazard event, often expressed as damage ratio or monetary loss. While damage functions for floods and seismic hazards have gained considerable attention, there is little knowledge on how drought intensity translates into ecological and socio-economic impacts. Reasons for this are different types of drought (meteorological – agricultural – hydrological – socioeconomic drought) and the complexity of drought propagation, leading to multifaceted impacts. Additionally, drought impacts are often non-structural, hard to quantify or monetarize, data on impacts is sparse, and there is a vast range of drought indicators characterizing the hazard.



The aim of this study is to explore the potential of designing "drought impact functions" for different case study areas in the UK, Germany, and the United States. To account for the multidimensionality of drought impacts, we use the broader term "drought impact function" over "damage function".

Step 1: Identify drought impact variables

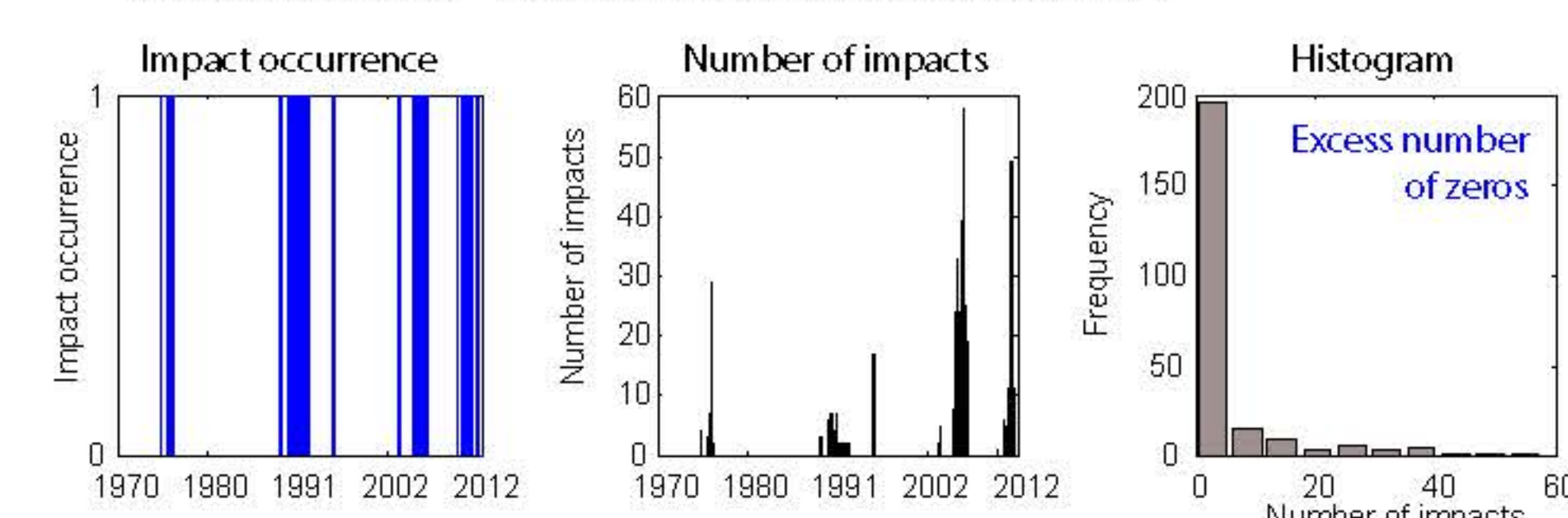
Sources of information on drought impacts/damage/loss

- Textual evidence of drought impacts
 - US Drought Impact reporter
 - European Drought Impact report Inventory (EDII)
- Agricultural yield data
 - Vegetation stress indicators via remote sensing
 - Monetary loss (e.g. via EM-DAT)

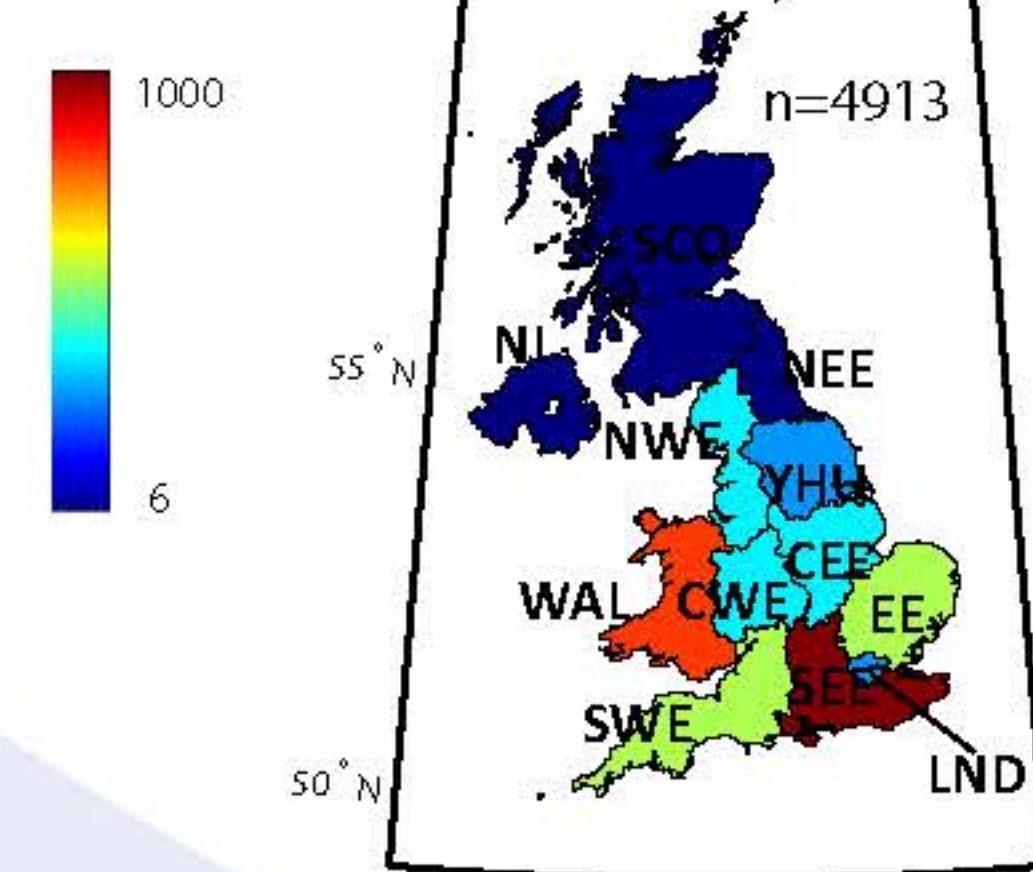
Quantification of text-based impact information, e.g.

- Impact occurrence (yes/no)
- Number of impact occurrences

Example: NUTS1* region South-East England (SEE)



UK: Number of impacts 1970-2012



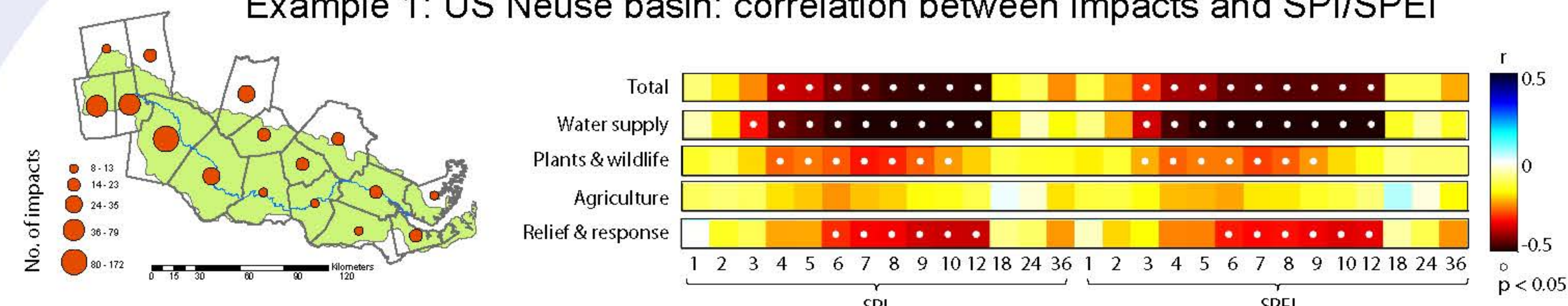
For the analysis text-based data was converted into monthly time series of number of impact occurrences per spatial unit (e.g. per county, basin, or NUTS region). Agricultural yield data was taken from EUROSTATS and the German Regionaldatenbank.

*NUTS: EU nomenclature of territorial units for statistics

Step 2: Identify meaningful drought indicators

Different drought indicators were evaluated: 1) Standardized Precipitation Index (SPI) of different timescales, 2) Standardized Precipitation Evaporation Index (SPEI) of different timescales, and 3) streamflow percentiles.

Example 1: US Neuse basin: correlation between impacts and SPI/SPEI



Effect of impact category

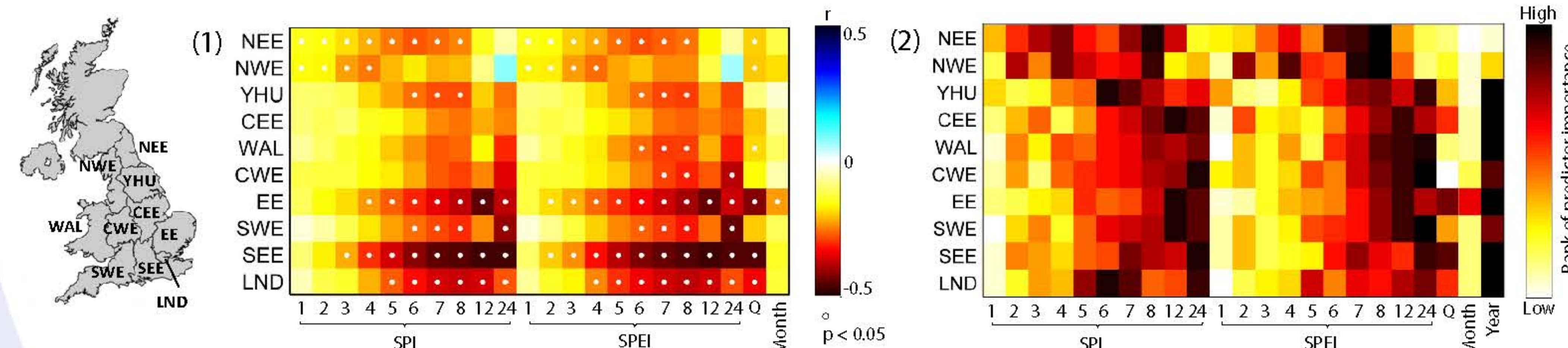
Correlation between monthly time series of number of drought impacts in the Neuse basin (North Carolina, USA) and SPI/SPEI of different timescales for the time period 2005-2012.

Data: Monthly timeseries of number of drought impacts and different indicators (SPI, SPEI, streamflow percentiles (Q)) for the time period 1970-2012.

Random forest approach: how it works

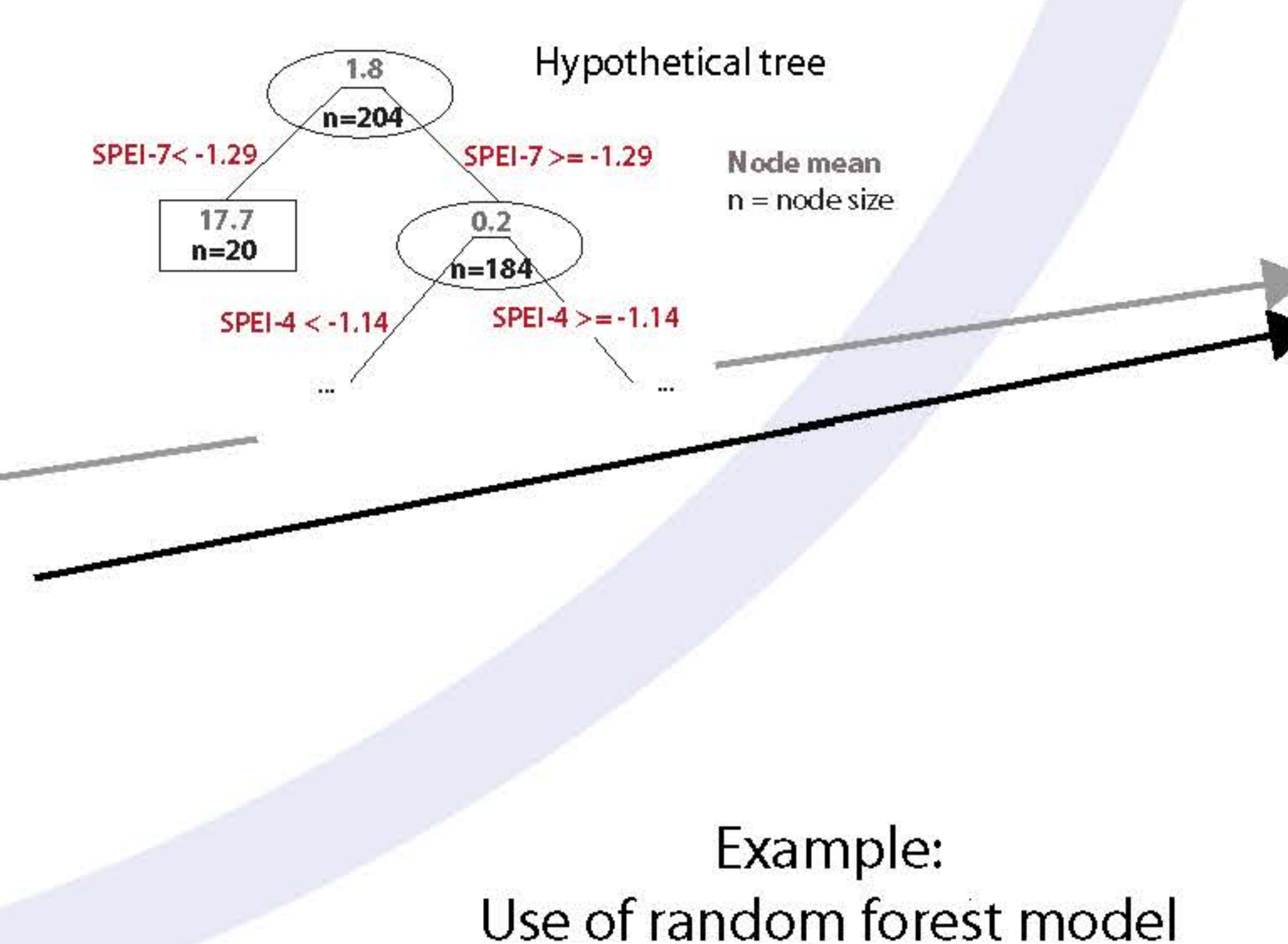
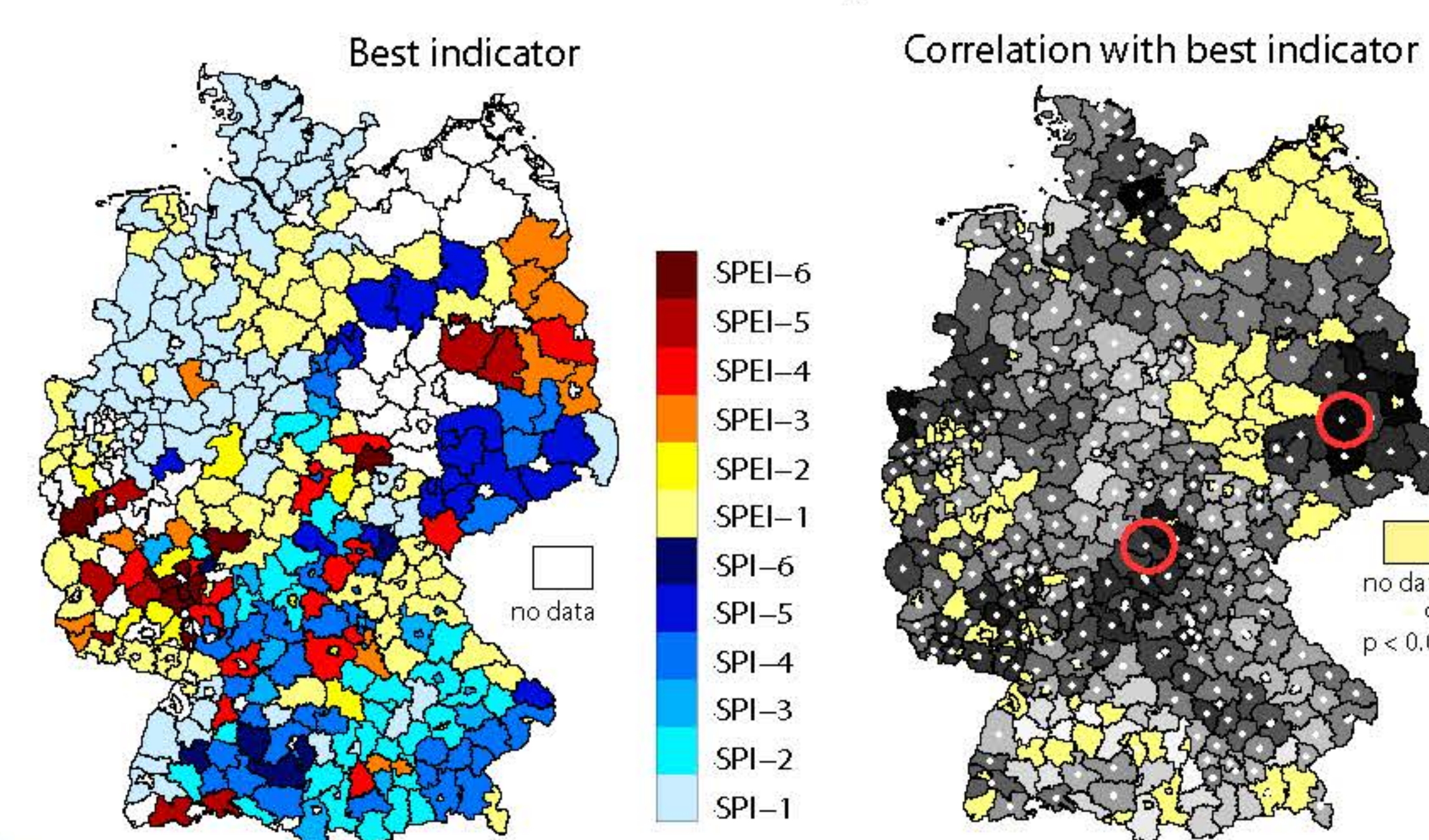
A regression tree explains the variation of a response variable by recursively splitting the data into more homogeneous nodes based on combinations of explanatory variables. A "random forest" (Breiman, 2001) represents a machine learning algorithm, where a large number of regression trees are grown on a bootstrapped subsample of the data (~2/3). The remaining data ("out-of-bag") are used to estimate the prediction error and the importance of each predictor variable.

Example 2: UK major socio-economic regions: correlation (1) and random forest approach (2)

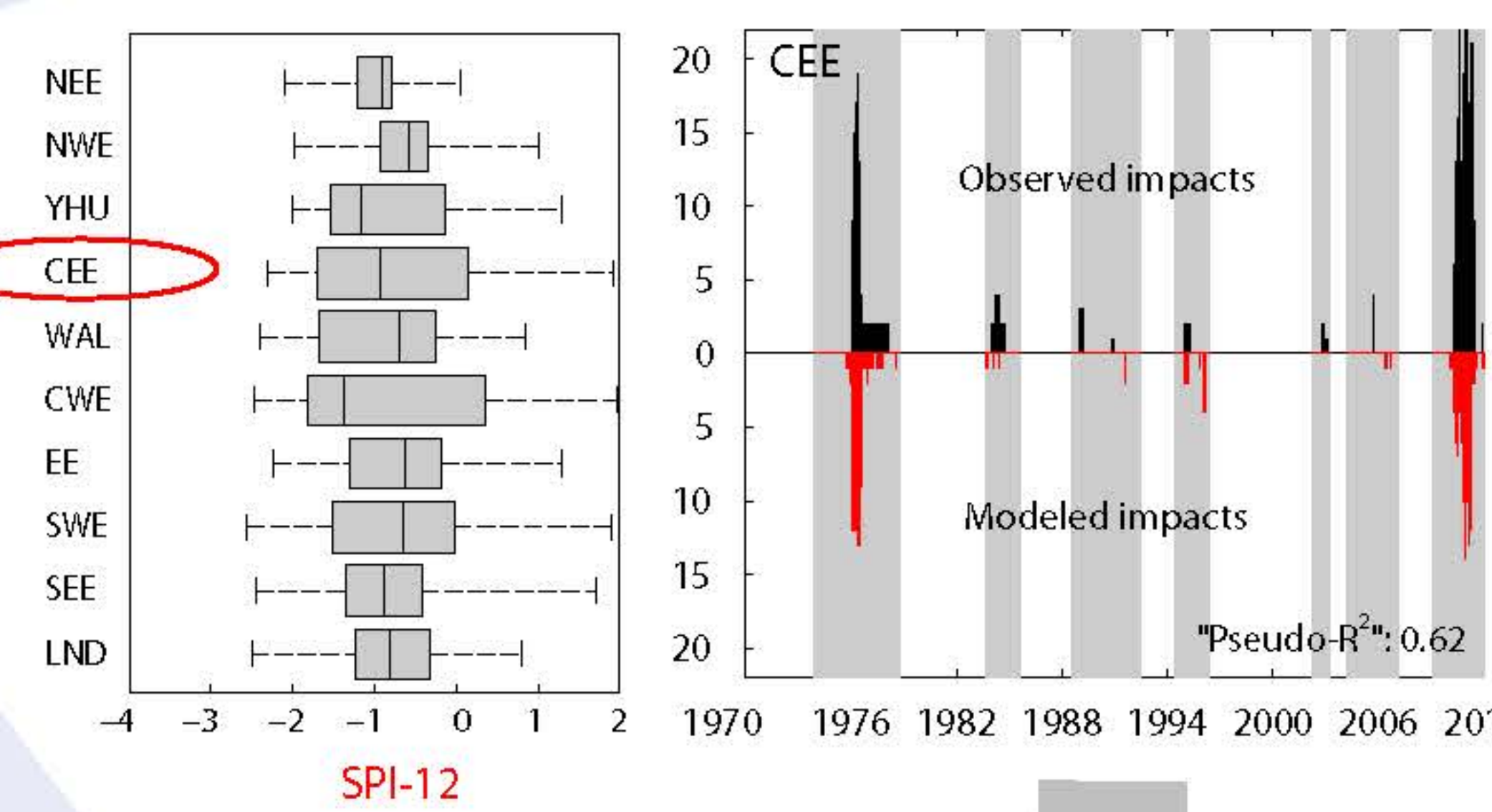


Example 3: Germany NUTS3* regions: correlation between wheat yield and SPI/SPEI

Correlation between annual time series (1999-2013) of winter wheat yield departure (detrended yield) per NUTS3 region and SPI/SPEI of different timescales. The left maps displays the drought indicator with the highest correlation (best indicator). The right map depicts the strength of correlation for the best indicator.



Example: Use of random forest model



The left graph displays the splitting values of SPI-12 during the random forest tree building per NUTS1 region in the UK, which can be interpreted as thresholds for impact occurrence. The median of the threshold distributions ranges around an SPI-12 value of -1 for most NUTS1 regions, which could serve as reference threshold for impact occurrence. The right graph shows observed versus modeled number of impacts for Central East England (CEE).

Summary of results

Evaluating drought indicators with text-based information on drought impacts or agricultural yield data has the potential to identify drought indicators, which are meaningful for drought impact occurrence.

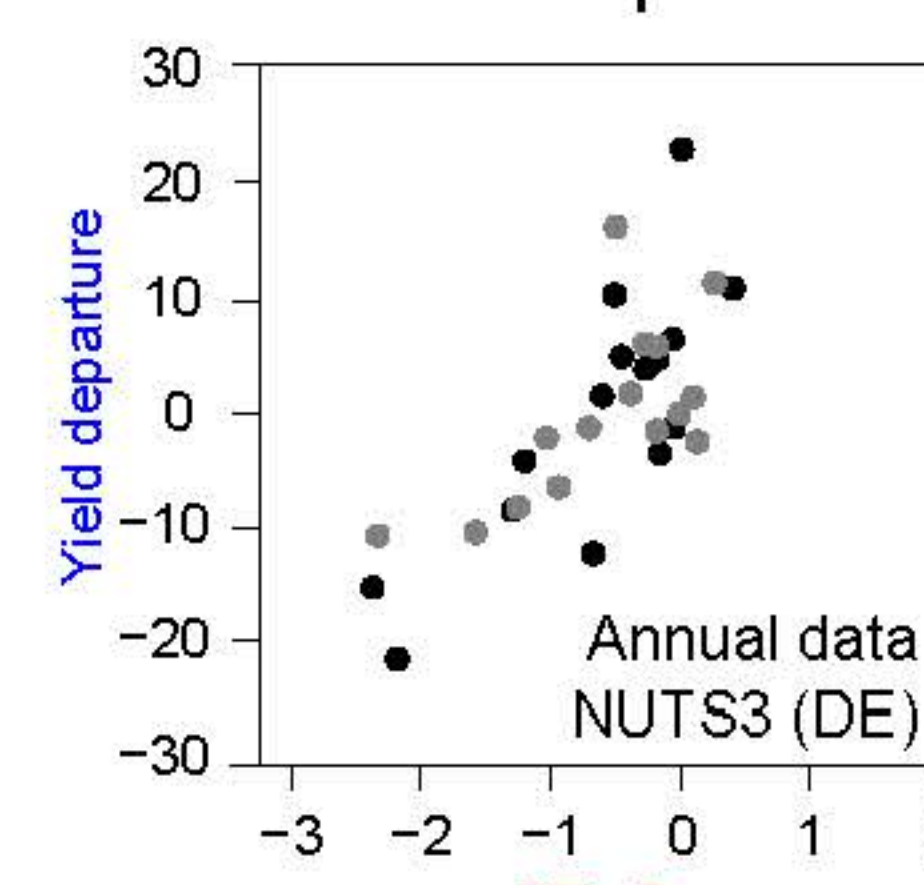
The analysis shows that the indicator(s) most representative for drought impact occurrence are

- sector or impact type specific (see example 1 step 2)
- region specific: different "best" indicators for the UK, Germany, and the US Neuse basin, and variability within the UK and Germany (see examples 2 and 3 step 2).

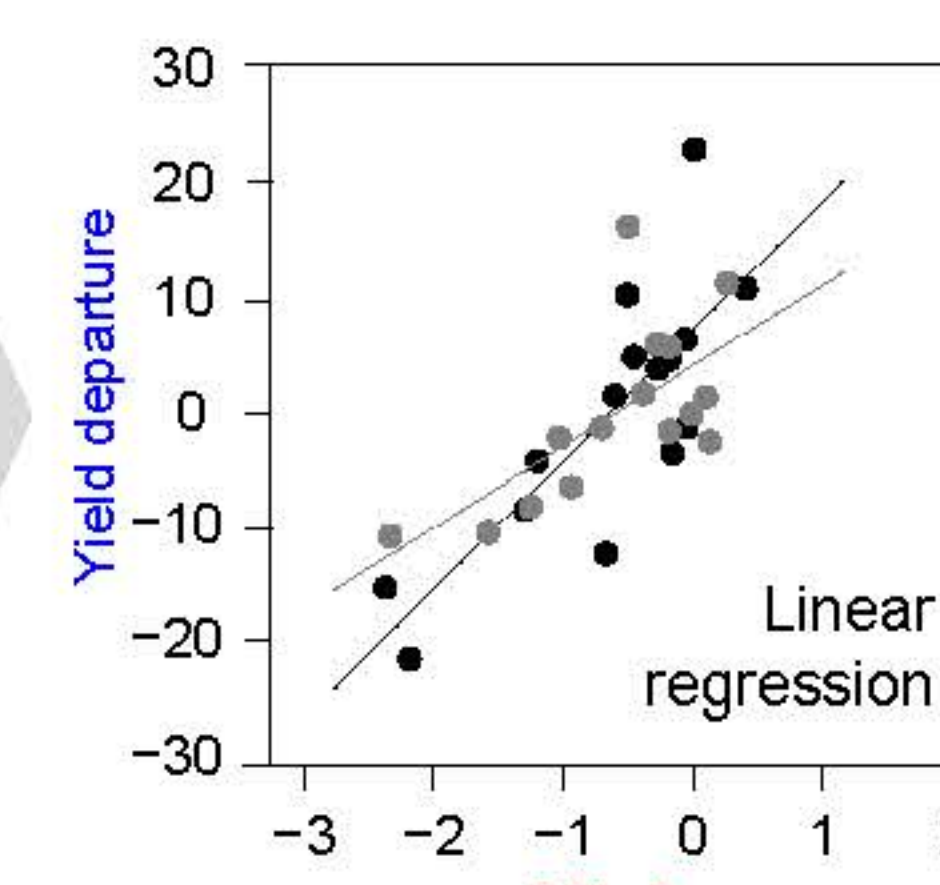
The purpose of designing drought impact functions in this study was to identify indicator values representing thresholds of impact occurrence, and to serve as basis for scenario construction. Preliminary analyses using different approaches show promising results in this direction but more research is needed on the effect of the choice of impact variable and statistical model.

Step 3: Design impact functions

Indicator vs. impact variable

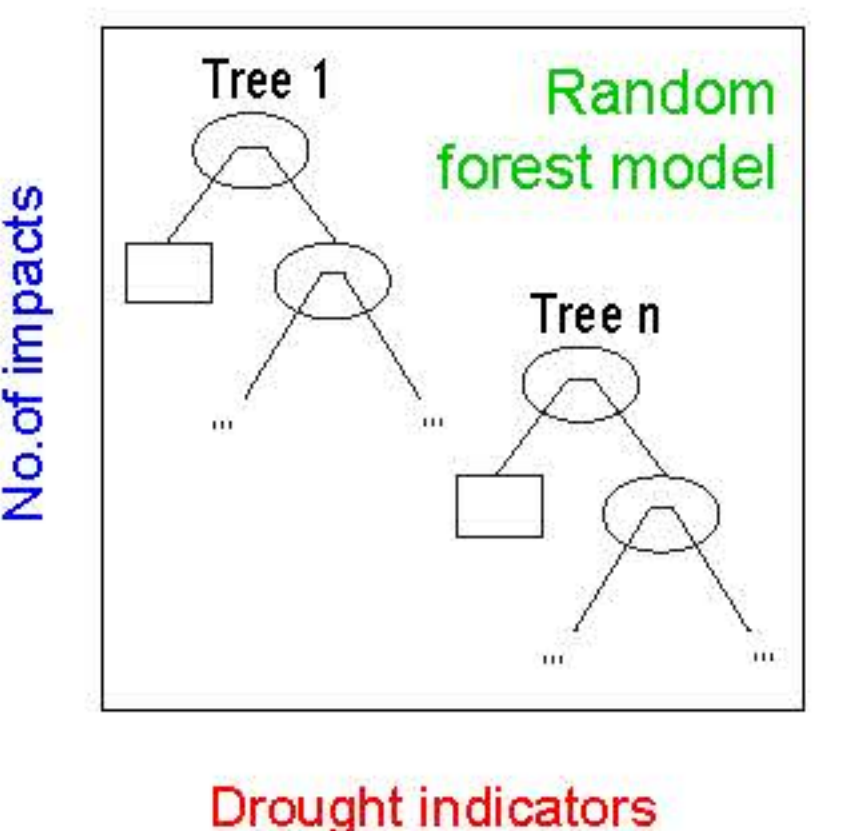
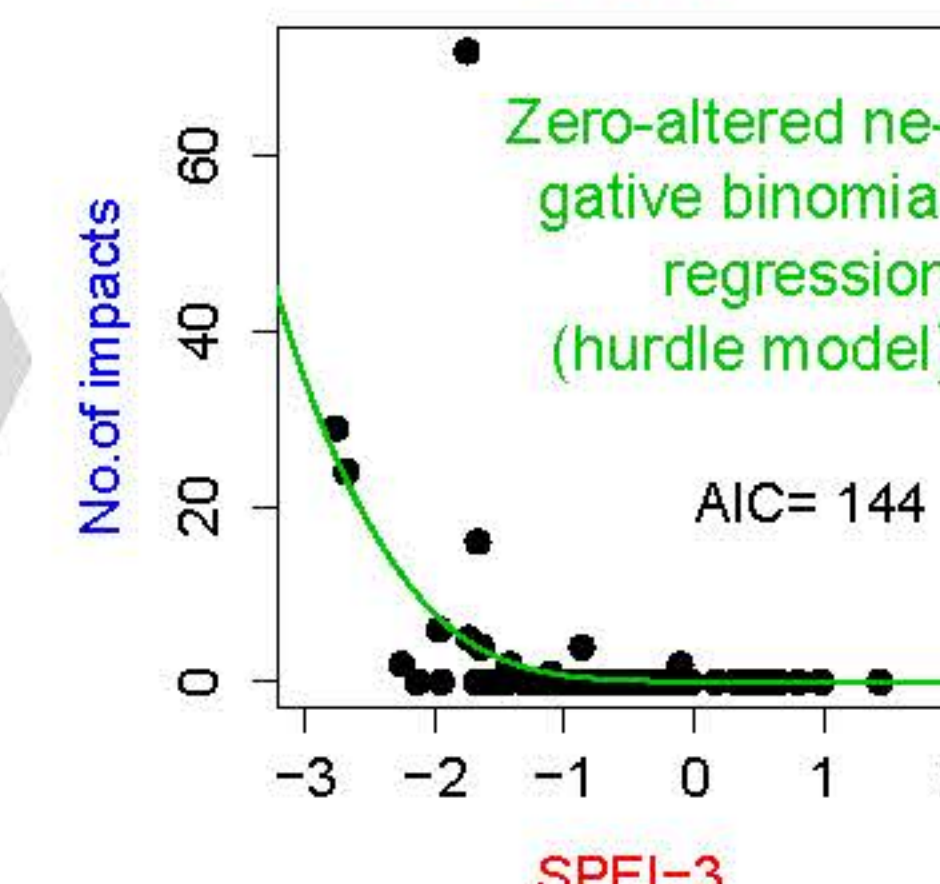
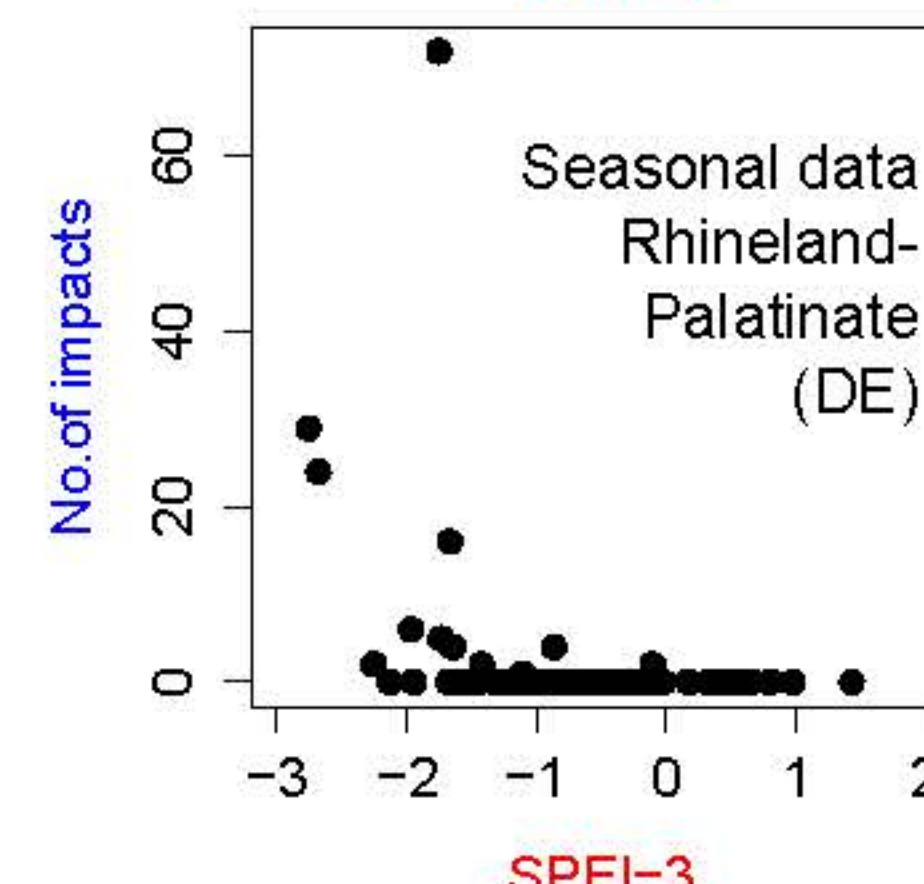
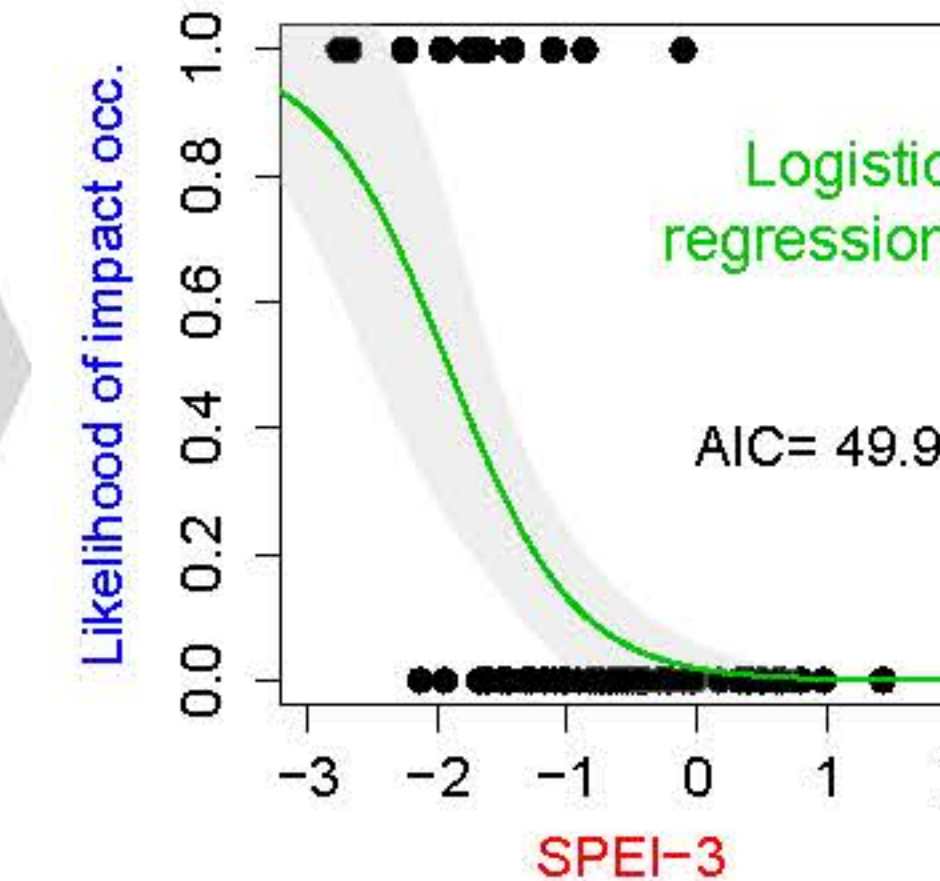
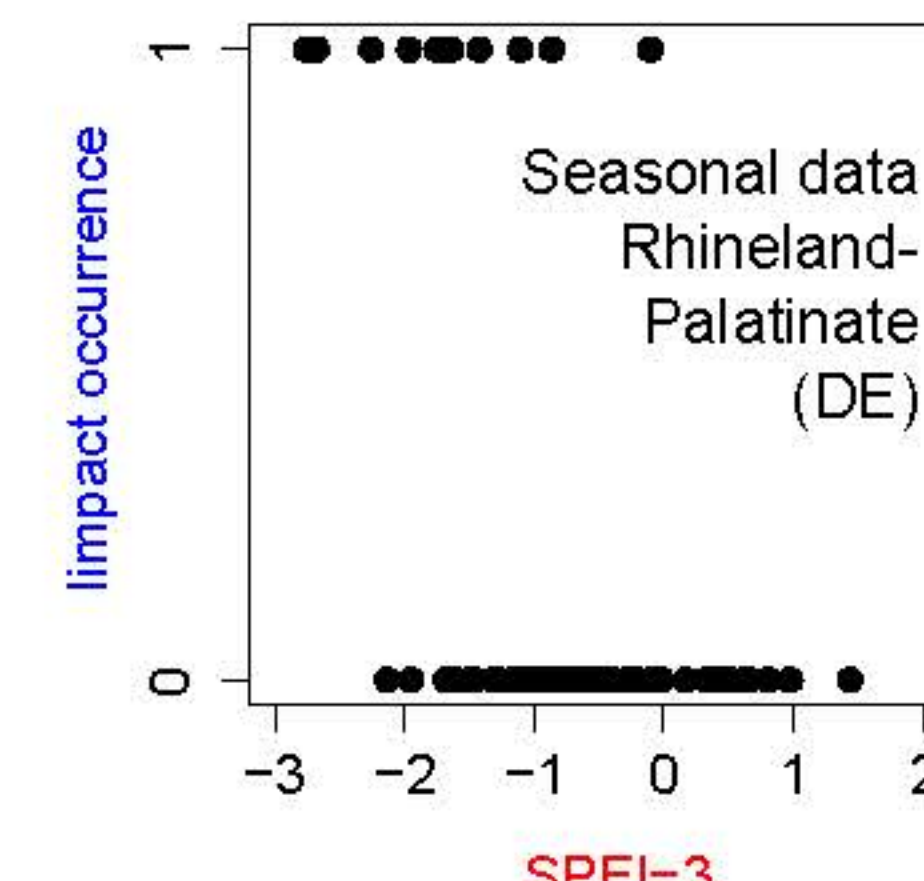


Potential model



Depending on the impact variable different parametric and non-parametric statistical models can be applied to derive impact functions.

The excess number of zeros in the impact data needs to be accounted for, e.g. via hurdle models (i.e. binomial distribution for modeling impact occurrence, Poisson or negative binomial distribution for count data).



Conclusion

The investigation of representative drought impact variables, meaningful indicators, and methods for linking indicators with impacts shows the feasibility of designing drought impact functions that are region and/or sector specific. Knowledge on how a certain hazard intensity translates into different negative consequences of drought may provide guidance for inferring meaningful triggers for drought monitoring and early warning and could have potential for a wide range of drought management applications, e.g. scenario construction for testing the resilience of drought plans.

Acknowledgements

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