Response to the review comments of the manuscript "A quantitative analysis to objectively appraise drought indicators and model drought impacts"

We thank the editor and both reviewers for their constructive comments and help to improve the manuscript. We revised the manuscript according to all comments and included most points without reservation. Below please find a point-by-point response to all comments.

1 Response to the editor's comments:

I believe the authors' comments in response to Referee #1 are convincing and I agree with their decision to try and keep hydrological indicators in the manuscript. Additionally, I would suggest adding vertical lines in Figures 3-7 to (1) distinguish meteorological from hydrological indicators and (2) maybe also distinguish SPI from SPEI indicators (and Q from Y).

→ Thank you for further suggestions how to improve the readability of the figures. We added the vertical lines in Figures 3-7.

Like referee #1, I would also appreciate to read a shorter version of section 5, even if all what is discussed there is of much interest. The challenge is therefore to make it more synthetic.

→ We shortened both the results and the discussion section by omitting some details and examples. Previously, we had 25.5 pages up to the conclusion section; we reduced the length to 22 pages up to the conclusion section. Since reviewer 1 suggested to add more findings to the conclusion section this section is now slightly longer.

Concerning the quality of data used, it would be worth mentioning the (relatively high in the two studied countries) underlying density of stations in the gridded E-OBS dataset.

→ We added this to page 6, L16-18

Authors' comments in response to Referee #2 (W. Pozzi) appear also satisfactory. About the choice of NUTS1 region, it would be maybe useful to warn against a potential effect of the size range and type of regions (e.g. in Germany, BE vs BV).

→ We feel the potential effects of size and type of region may not warrant a detailed warning as this could be rather speculative and potentially rather lengthy while still not providing any hard evidence of the effects. We transparently show the size of NUTS1 region in Figure 1, and now also specifically draw the reader's attention in section 2.1 to the fact that the different sizes of regions are shown in this Figure. We hope this satisfies the editor.

On the criticism about the reference to individual indicators, one way to make the tree approach clearer, I would suggest to explicitly show one of these decision trees as an example, possibly in the supplementary material or annexes. I may be useful for those readers not accustomed to random forest analyses.

→ Reviewer 1 stressed that we provided too much detail about the random forest (RF) method, which is nowadays relatively widely used. We therefore deleted some of the details, but moved the bulk of the text to an appendix. We think that because the RF method is widely used and many papers exist using this method, there is no need to provide further plots of single regression trees. A few examples of current studies using RF models in the context of environmental analysis in addition to the ones cited in our manuscript are:

Spekkers et al., 2014, doi:10.5194/nhess-14-2531-2014; Catani et al., 2013, doi:10.5194/nhess-13-2815-2013 ; Appelhans et al., 2015, http://dx.doi.org/10.1016/j.spasta.2015.05.008; Rodriguez-Galiano et al., 2011, doi:10.1016/j.isprsjprs.2011.11.002; Hill et al., 2014, doi:10.1007/s10584-014-1174-4

Also, we are worried about potentially misleading conclusions when we show individual trees. Each tree is based on only a subset of data and only a subset of splitting variables is tried. Hence, a single tree could look like not all indicators are being used.

The authors may want to change some of the vocabulary used in the manuscript, namely the word "trigger" that led Referee #2 to comment on the relation of such a "trigger" to drought indicator threshold. I believe that the aim of the manuscript is not to define such actually drought response triggers, but to find drought indicator thresholds that would serve as proxys for these triggers.

→ This is exactly the way we see thresholds and their potential use. We re-wrote section 5.2 (page 21) and hope this better reflects our intention. We also added new text to the same effect to the conclusion section.

Additionally, and following Referee #1 (but also Referee #2), I would suggest making the conclusion section a bit stronger, maybe by incorporating some material from the lengthy discussion section.

→ We added the details of the findings on best predictors, and on indicator threshold values.

2 Response to Referee #1

2.1 Response to major comments

Length:

The reviewer highlighted the need to shorten the manuscript, especially some parts of the methods, the results, and some discussion aspects. Thank you for making detailed suggestions on this. We moved parts of the description of the random forest methodology to an appendix. We also shortened the results and discussion sections, especially since the reviewer confirmed good interpretability of the figures. Previously, we had 25.5 pages up to the conclusion section; we reduced the length to 22 pages up to the conclusion section. Since the reviewer suggested to add more findings to the conclusion section this section is now slightly longer.

"Too much at stake":

Regarding the suggestion to move parts of the paper (streamflow and groundwater as additional indicators; random forest (RF) predictions) to a separate paper, we prefer to leave the structure as is, which was found acceptable by the editor. We think that evaluating hydrological indicators in addition to SPI/SPEI provides further insights. We also think that that the RF predictions add further value by providing the opportunity to learn about the EDII data, yet this would not make a separate paper. After shortening the manuscript in the suggested way we are confident that the readability has improved despite keeping the overall structure.

Uncertainty of EDII data:

It is correct that the impact report data has several sources of uncertainty and the quantification of this information as well. We discussed this transparently as the reviewer confirmed and this is also reported in other papers that we refer to (Stahl et al. 2015, NHESS; Bachmair et al. 2015, NHESS). Since the paper was suggested to be shortened, we would not like to further expand on this issue. The point of the paper is to explore the value of impact report data for indicator validation despite the obviously uncertain impact data. Also, the RF method (bootstrap sampling) provides a way to incorporate the uncertainty of the impact data.

Regarding other methodological choices (reviewer mentioned: regionalization, thresholds, aggregation, minimum number of events, indicators, etc.) we aimed to reduce the uncertainty of results. For instance, while the threshold of a minimum of 10 months with impact occurrence is arbitrary, it at least transparently discriminates areas with very little data, where the risk of drawing misleading conclusions may be higher. Regarding the aggregation of indicator data we would like to refer to a study by Bachmair et al. 2015 (NHESS) and additional work (as we already do in section 2.2. of the paper), where different metrics for spatial aggregation (mean, median, 10th percentile, maximum, % area in drought) were investigated and resulted in only minor differences.

Quality checks of indicator data:

The E-OBS data used for SPI and SPEI calculation is a published data set and we refer to Haylock et al. (2008) for detailed information about this data. For Germany, streamflow and groundwater data used were the officially published data by the authorities that produced or provided the products or data and data were quality controlled and homogenized by the providers. For the sake of comparability with other studies it does not appear useful to apply further corrections in addition. For UK streamflow data, the National River Flow Archive staff quality control UK streamflow data as part of an annual data acquisition process, any queries are returned to measuring authorities to be resolved before data is loaded to the NRFA and released for general use. We therefore believe the indicator data are of good quality. Further, the spatial aggregation (mean) of indicator data over the NUTS1 regions will smooth the input data, meaning that any local discrepancies would be difficult to detect.

2.2 Response to specific and technical comments

Abstract

- P9438 L14 You can remove "random forest", the general kind of method is enough in the abstract. → changed
- P9438 L18 Two hydrological indicators: please, name them in the abstract. → changed

Introduction

- P9349 L7 Avoid words like "creeping" in a scientific paper. → drought has been referred to as “creeping” phenomenon in numerous papers following Gillette 1950, but we changed it to “insidious”
- P9440 L18-20 Some typo errors in this sentence. → we don’t see where
- P9441 L16 Which other types? Briefly list them besides the citations. → we added “such as wildfires, or impacts on public water supply or the energy and industry sector” as examples (a comprehensive list of all impact types would be too lengthy)

Data

- P9443 L22-23 These indicators are important, but you name them for the fist time after a few pages. I suggest to cite them also in the abstract or at least in the introduction. → added to the abstract
- P9444 L1 The EOBS have been subsequently updated till version 12. Every version shows a not marginal improvement in terms of data quality and quantity. Have you just used the gridded data as they are or have you performed quality checks or homogeneity tests? Though the problems of earlier versions are mostly out of your areas of interest (i.e., UK and GER), some robust quality test before the use would be desirable. → We used the gridded data as is. The E-OBS data used for SPI and SPEI calculation is a published data set and we refer to Haylock et al. (2008) for detailed information about this data. We added the following sentence, as suggested by the editor: “For the UK and Germany the underlying station density of the gridded data is relatively high within Europe, and the dataset is based on more European observing stations than in other European or global datasets (Haylock et al., 2008).”
- P9444 L4-10 Why didn’t you choose a common reference period? At least for each country. → The reference period for the UK is in accordance with data coverage of the UK National River Flow Archive and thus differs from the reference period for SPI and SPEI, and streamflow and groundwater level percentiles in Germany. Both the rank correlation and the random forest approaches make use of the relative, rather than absolute, magnitude of the values, so the difference in reference period will not affect the results.
- P9444 L13-26 Have you checked the quality with your own tests? this would enhance the reliability of the outputs, as they strongly depend on the quality of input data. → see response to the more general comment on data quality checks
- P9445 L15 How can you be completely sure that such impact (e.g., crop loss for that year) depends on drought, should it be partially or totally dependent? Because in a previous paragraph you said that it’s not easy to understand how drought impacts many sectors because the cause of such an impact (crop loss, for example) is often unclear or undetermined. I mean, your effort is relevant, but how you decide to use a document in the EDII in your calculations? Is there a selection? Are all the entries considered? Are some possible entries discarded before being included into the EDII database? It seems to me that you did a considerable effort in collecting

the impacts, so you might want to briefly report about this selection also in this paper (not only citing the proper reference), in order to convince the readers that the input for the calculations shown in this manuscript are robust. → The text-based impact reports in the EDII per definition contain information about a negative affect due to drought. There are guidelines for entering drought impact reports in the EDII. We do not want to add more text to the already lengthy paper. The cited paper Stahl et al. 2015, NHESS, provides more information about the drought impact data. Please also refer to the response to the general comment on the uncertainty of EDII data.

- P9447 L14-16 How do you think this lack of reported impact may affect your calculations? though you only selected regions with at least 10 months of impacts, do you think that this lack could bias the models or the outputs even for these regions? → Since we cannot be sure whether missing data is due to no impacts or no reports (or not finding these reports) we conducted the "RF Backwards Learning" analysis to get a better understanding about this issue. Please also refer to the response to the general comment on the uncertainty of EDII data.
- Methods P9449 L15 - P9450 L6 In my opinion you go too much in details with random forest steps. Just cite the method and summarize in a couple of short sentences how it works. → Changed accordingly; we moved most of the RF methodology to an appendix, and deleted some text.

<u>Results</u>

- P9454 L8 what's your opinion on this fact? Is it due to lack of reported impacts regarding other seasons? Lack of impacts? I'm interested in your opinion, I'm not arguing on this fact. → Most droughts in Germany represent summer droughts and thus only very few drought impacts in the fall/winter (e.g. see analyzed drought events in Bachmair et al. 2015, NHESS).
- P9458 L1-10 what do you exactly mean for "false-positive impacts"? Predicted/modeled impacts that did not effectively occur? A simple point could be: no impacts occurred or no impact reports have been included into the EDII? → We defined what we mean by this in L2-4: "They expose instances of potentially "false-positive impacts", i.e. a positive number of impacts is modeled while there are no observed impacts." The reason for this likely is that impact reports are missing in the EDII. The RF Backwards Learning analysis was conducted to specifically scrutinize whether missing impacts in the EDII are likely due to missing data (indicated by such instances of "false-positive impacts") or due to true absence of impacts.
- P9458 L13- 14 So the aggregation at NUTS1 may be a limit? Moving to NUTS2 would limit the "false-positive" records? This section seems a bit too long in my opinion. → 1) Regarding the NUTS1 level issue: The second reviewer also highlighted the issue of spatial aggregation at the NUTS1 level. Please refer to the response to this general comment and respective changes in the manuscript. Moving to an even smaller scale could potentially lead to more instances of "false-positive" records since less data is available at this smaller scale. We added further information on reason for the choice of NUTS1 region level for analysis to section 2.1; 2) Regarding length: We followed the recommendation to cut length and deleted details about "false-positive impacts" in Germany (section 4.4 → removed last paragraph).

<u>Discussion</u>

- P9459 L12-14 These potential EDII error sources seem the most limiting factor, despite the remarkable validity of your analyses. → please refer to the response to the general comment on the uncertainty of EDII data
- P9461 L13-29 your observations are interesting, but at this point it seems that studying meteorological drought indicators as the SPI and the SPEI and studying in parallel streamflow and groundwater drought indicators is a really difficult task and it may be considered a splitting of these two main kinds of indicators into two different papers. This is not a suggestion, but the results shown in this paper are too many and sometimes it's not easy to follow a path during the long chapters. → We believe that keeping both meteorological and hydrological indicators adds

further insights; the editor encouraged us to keep both types of indicators as well. We are confident that the shortening of the respective sections has improved readability.

- P9462 L1-5 However I do recognize the overall validity and complexity of your work and I agree with this comment. → we are glad the reviewer agrees with this
- P9462 L20 Should you just choose one, which one would you suggest? Personal curiosity. → Does this refer to the indicator thresholds? It depends on the purpose, e.g. whether to issue only a warning (the mean or the median in this case may be “a safe guess”), or to trigger some action (possibly better linked to stronger severity, e.g. 75^{th} percentile).
- P9463 L6 why? To simplify the calculations? To focus on "long seasonal events/impacts"? → Do you refer to the uncertain timing of the impacts? Many impact reports do not specifically state the end of the impact; also it is generally not easy to determine the termination of an impact, e.g. when have forestry drought impacts receded? We describe the procedure of assigning the temporal occurrence of impacts in the methods section.
- P9463 L24- 25 This is crucial and maybe it is discussed a bit "too far" in the manuscript. → we deleted parts of this paragraph
- P9465 5.3 Personal taste: learnt instead of learned. → left as is (subject to discretion of HESS house style)
- P9467 L10 This subchapter 5.3 in my opinion is too long, you could evaluate the possibility to summarize the entire chapter in a couple of sentences in the conclusions and dedicate a brand new paper which preliminary explore the suitability of RF method applied to drought impacts. This kind of topic surely deserves a dedicated study and I would be really glad to read it.and I’m sure that I’d not be the only one sharing this opinion. → We significantly shortened this section as suggested. However, we prefer to keep the general structure as is and not transfer this part of the analysis to another paper.

<u>Conclusion(s)</u>

- Use plural, if you please. → changed to “conclusions”
- P9467 L20-23 I would say additional empirical evidence, because these findings are not new to scientific community. You might also add a couple of citations here. → added “additional” empirical evidence; we prefer to not add references here but we have references in the respective discussion part
- P9648 L9 Compared to the length of chapters 4 and 5, the conclusions in my opinion are too short and do not effectively summarize the most relevant findings except of a fast recall of concepts analyzed. Improving conclusions might help the appeal of the paper, because some readers (let’s blame on them, by the way) just read the abstract, skip the core text, and jump to conclusions. → we added further relevant findings as suggested

3 Response to Referee #2

1) Choice of NUTS1 region level for analysis and impact/indicator aggregation:

The reviewer is certainly right that the NUTS1 region level does not correspond to local-scale information. However, it integrates that information at this scale. Many studies have shown that drought signals (e.g. compared to floods) are regional to large-scale. There have been several studies for the UK and Germany that grouped regions affected by drought based on precipitation, streamflow and groundwater revealing homogenous responses across regions larger than the typical NUTS-1 region (e.g. Hannaford et al. (2011), doi:10.1002/hyp.7725; Burke and Brown (2010), JOH; doi:10.1016/j.jhydrol.2010.10.003). Furthermore, most monitoring and early warning systems cover continental scales and are found useful by a range of users. The target for this study is not the local scale but represents a first attempt at an overview of “ground-truthing” drought indicators with impact information.

The NUTS1 region level (major socio-economic regions) was chosen because of a lack of sufficient data for analysis with finer-scale resolution. We initially explored the potential of using NUTS3 or NUTS2 level data but data availability did not permit the analyses we conducted in this study using NUTS1 level data. Upscaling to the NUTS1 region level was thus necessary. However, it needs to be pointed out that a large portion of impact reports only makes reference to the NUTS1 region and not to smaller scales. In the introduction we state that “the aim is to develop methods that can be extended to other geographical areas in future applications”. In fact, with potentially better data availability in the future the applied methods could be used for more local-scale analyses in addition to further geographical areas. Further data may also allow more detailed analyses for different types of impacts.

We acknowledge the recommendation to explore NUTS1-2-3 level interactions (review comment on “assessment of how many reports would have to actually be prepared (how larger a sample size) would be required in order to resolve some of these impacts at the NUTS2 and NUTS3 level”) but refrain from it given the already lengthy paper, as was stressed by reviewer 1. Please note that the numbers in the figures from the Stahl et al. (2012) DROUGHT-R&SPI report, which were presented in the review comment, are outdated by now since many impact reports have been added to the European Drought Impact report Inventory. We also want to point out that we are aware of the effect of drought indicator aggregation to NUTS1 level, as evidenced by the paragraph discussing potential reasons for a low correlation between drought impacts and streamflow/groundwater levels (page 9461); hence we think we are sufficiently transparent about this.

To address this review comment, we added further information regarding the reason for selecting the NUTS1 region level in the methods part (2.1.) and are grateful to the reviewer for pointing out the need to provide this information.

2) Identification of indicator thresholds and their potential use:

There are two points of criticism: first, that the used indicator thresholds solely represent single drought indicators, while a single indicator likely is not sufficient for capturing the multifaceted drought hazard; second, the potential use of the identified thresholds derived for the NUTS1 level may not be relevant for guidance in drought management plans because such triggers should be grounded at the local level.

Regarding the first point of criticism it needs to be clarified that the figures indeed show splitting values during random forest (RF) construction for individual indicators, but this is for presentation purposes; however, we want to emphasize that the models are all based on multiple drought indicators. A tree approach with multiple indicators has, in our opinion, even an advantage over a pre-defined combined drought index. It accounts for multiple conjunctional causality and allows us to describe different combinations of multiple indicators that eventually lead to an impact. Hence, the splitting values per indicator are extracted from models considering multiple predictors and possible interactions, e.g. while for the root node SPI-3 with a certain splitting value may represent the best discriminator, for a finer-split node a different SPI or SPEI accumulation period and corresponding threshold may be selected. Therefore the derived median of the splitting value distribution, which we regard as a threshold representative for impact occurrence, factors in multi-predictor interactions. We hence disagree that the presented thresholds represent single indicators only and that they be omitted from the paper. Instead they represent splitting values that are conditional on other drought indicators as predictors. We thank the reviewer for the valuable comment because this shows that this point was not clear in the paper. We added this information to section 3.2 and 4.3 (page 11 L13-15 – page 14 L21-22).

Concerning the second point we want to emphasize that the purpose of identifying indicator thresholds representative for impact occurrence is to 1) complement and allow comparison with local-scale decision making that is usually based on stakeholder knowledge or the experience of individuals, and 2) to provide an impact-driven perspective of indicator thresholds in addition to common hazard intensity classes 'passed-on' through time (e.g. SPI-n < x demarking mild/moderate drought). We stress that the identified thresholds are by no means meant to replace (or "short cut", as the reviewer stated) drought triggers identified by stakeholders. We re-wrote section 5.2.

The reviewer particularly articulated the concern that the thresholds for streamflow may not be useful because these often correspond to localized impacts. To address this concern we could potentially omit the plots showing streamflow and groundwater level thresholds. However, since neither the other reviewer nor the editor suggested this was necessary, we have left the plots in the paper. It is worth noting that the thresholds for meteorological indicators (especially for longer aggregation periods) will be informative for impacts that are less localized (e.g. not occurring just within a single river).

3) Identified conclusion

The reviewer noted that "The real main conclusion of their study is: "Agricultural and hydrological drought impacts were generally best linked to shorter and longer SPI (and SPEI) time scales, respectively. Here, shorter and longer refer to 1-4 (Germany) and 7-8 months (England)." We feel this paper covers more than this brief conclusion but in essence this particular issue is discussed in detail on pages 9460/9461.

4) "The Groundwater Issue"

It is correct that we did not standardize streamflow or groundwater level data but used percentiles instead. However, since we apply rank correlation this does not affect our results. We also discussed possible reasons for lower correlation between impacts and streamflow/groundwater levels in the paper (see comment above).

A quantitative analysis to objectively appraise drought indicators and model drought impacts

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Abstract

Drought monitoring and early warning is an important measure to enhance resilience towards drought. While there are numerous operational systems using different drought indicators, there is no consensus on which indicator best represents drought impact occurrence for any given sector. Furthermore, thresholds are widely applied in these indicators but, to date, little empirical evidence exists as to which indicator thresholds trigger impacts on society, the economy, and ecosystems. The main obstacle for evaluating commonly used drought indicators is a lack of information on drought impacts. Our aim was therefore to exploit text-based data from the European Drought Impact report Inventory (EDII) to identify indicators which are meaningful for region-, sector-, and season-specific impact occurrence, and to empirically determine indicator thresholds. In addition, we tested the predictability of impact occurrence based on the best performing indicators. To achieve these aims we applied a correlation analysis and an ensemble regression tree approach~~ ("random forest"),~~, using Germany and the UK (the most data-rich countries in the EDII) as a testbed. As candidate indicators we chose two meteorological indicators (Standardized Precipitation Index (SPI) and Standardized Precipitation Evaporation Index (SPEI)) and two hydrological indicators~~.~~ (streamflow and groundwater level percentiles). The analysis revealed that accumulation periods of SPI and SPEI best linked to impact occurrence are longer for the UK compared with Germany, but there is variability within each country, among impact categories and, to some degree, seasons. The median of regression tree splitting values, which we regard as

estimates of thresholds of impact occurrence, was around -1 for SPI and SPEI in the UK; distinct differences between northern/northeastern versus southern/central regions were found for Germany. Predictions with the ensemble regression tree approach yielded reasonable results for regions with good impact data coverage. The predictions also provided insights into the EDII, in particular highlighting drought events where missing impact reports may reflect a lack of recording rather than true absence of impacts. Overall, the presented quantitative framework proved to be a useful tool for evaluating drought indicators, and to model impact occurrence. In summary, this study demonstrates the information gain for drought monitoring and early warning through impact data collection and analysis~~, and~~. It highlights the important role that quantitative analysis with impacts data can have in providing "ground truth" for drought indicators, alongside more traditional stakeholder-led approaches.

1 Introduction

Drought is less tangible than other natural hazards, such as earthquakes or floods, due to its slow onset, ~~"creeping"~~insidious nature, and complex, often non-structural impacts (Gillette, 1950; Wilhite et al., 2007). Nonetheless, drought is known to affect more people than any other hazard, and to cause high economic loss (Loayza et al., 2012; Wilhite et al., 2007). While droughts cannot be prevented, societal vulnerability can be reduced, with monitoring and early warning (hereafter, M&EW) being one important measure to enhance drought resilience. The aim of M&EW is to provide adequate and timely information on drought conditions to enable people and organizations to be better prepared and react accordingly (Svoboda et al., 2002; Wilhite and Svoboda, 2000). Such systems are usually based on several drought indicators representing different domains of the hydrological cycle, i.e. indicators for meteorological drought, soil moisture drought and vegetation stress, hydrological drought, and groundwater drought.

A recent trend has been the design of "combined" or "multivariate" indicators consisting of a blend of individual ones. The rationale behind the construction of blended indictors is that a single indicator is not sufficient to adequately capture different types of drought, and the corresponding multiplicity of drought impacts that differ markedly in response time (Hao and Singh, 2015). There have been several studies assessing the link between indicators of different types of droughts, e.g. between meteorological drought and streamflow, soil moisture, or remotely sensed vegetation stress indicators (Haslinger et al., 2014; Ji and Peters, 2003; Martínez-Fernández et al., 2015; Vicente-Serrano and López-Moreno, 2005; Vicente-Serrano et al., 2012). These are useful when there is an assumption that the lag between, say, meteorological and hydrological drought represents the response time for impact occurrence in, say, riverine ecosystems. Drought indicator choices can be substantiated by stakeholder consultation or expert judgement, as has been implemented for the operational US Drought Monitor (Svoboda et al., 2002). Similar initiatives have been developed in research project settings in southwest Germany (Stölzle and Stahl, 2011) and Switzerland (Kruse et al., 2010).

However, while indicators representing different types of drought are commonly used as proxies for impact occurrence, there is, to date, little empirical evidence as to which indicator best represents drought impact occurrence for any given sector. Lackstrom et al. (2013) identified an impact-driven perspective as the "missing piece" of drought monitoring; what is of ultimate interest is knowledge of when and where a precipitation shortfall or low streamflow or groundwater level will translate into impacts on society, the economy, and ecosystems. A direct, empirical evaluation of drought indicators with impact information would obviate the need for assumptions based on intercomparing different drought indicators.

Aside from identifying indicators important for drought impacts, there is a need for a better understanding of the meaning of indictor thresholds used for drought declaration and as triggers for management actions in drought plans. Such thresholds are mostly based on hazard intensity classes corresponding to a certain frequency of occurrence, e.g. following the widely accepted Standardized Precipitation Index scheme, with classes ranging from 0 to -0.99 (mild drought), -1 to -1.49 (moderate drought), -1.5 to -2 (severe drought), and < -2 (extreme drought) (McKee et al., 1993). The US Drought Monitor (USDM) differentiates between five drought severity classes based on several indicators and corresponding thresholds (Svoboda et al., 2002). Different thresholds again are used for delineating alert classes of the Combined Drought indicator of the European Drought Observatory (European Drought Observatory, 2013).

Common to all thresholds is that they are arbitrary cut-off points (e.g. McKee et al., 1993; Svoboda et al., 2002). A survey among drought managers in the US on drought plans and respective indicators and triggers revealed that there is large uncertainty in the selection of thresholds, with one survey reply uncovering that most states selected their indicators "out of a hat" without knowing whether they "worked" (Steinemann, 2014). There is currently no consensus on appropriate drought indicators and thresholds meaningful for practitioners of different sectors.

Regarding drought prediction, a substantial body of research has been dedicated to forecasting drought indicators with sufficient lead time (e.g. Dutra et al., 2014; Mehta et al., 2014; Trambauer et al., 2014; Wetterhall et al., 2015). However, while the models used for forecasting may propagate the climate signal into soils and hydrology, they do not include a further link to the tangible negative environmental and socio-economic impacts of a particular drought. Models bridging the gap between drought indicators and impacts are rare. While predictions of crop yield are more common (e.g. Hlavinka et al., 2009; Mavromatis, 2007; Quiring and Papakryiakou, 2003), very few studies have tested approaches for modeling other types of drought impacts ~~(e.g.~~such as wildfires, or impacts on public water supply or the energy and industry sector (e.g. Blauhut et al. (2015), Stagge et al. (2014), Gudmundsson et al. (2014), and Vicente-Serrano et al. (2012)). The complexity of processes and the interconnectedness of the multitude of drought impacts, which may occur with much delay and even outside of the hazard affected area (Logar and van den Bergh, 2013; Wilhite et al., 2007), may be one reason why few drought impact models have been presented.

The most important obstacle, however, is a paucity of information on drought impacts. Initiatives to rectify this include the US Drought Impact Reporter (DIR) (Wilhite et al., 2007), and the more recently developed European Drought Impact report Inventory (EDII) (Stahl et al., ~~2012~~2015a). Both provide text-based, categorized information on reported drought impacts. The majority of impacts of the US DIR stem from online media clipping (Wilhite et al., 2007), meaning that it can be used as a real-time monitoring tool. In contrast, the EDII is designed as a research database with a focus on past drought events. Other potential sources of drought impact data are reported crop yields, or losses assembled in the Emergency Events Database EM-DAT (www.emdat.be) or by re-insurance companies. Nevertheless, crop yield reductions may not necessarily be due to drought and loss data mostly provides aggregated information on large events without details on the temporal and spatial evolution of impacts, which is essential for empirically validating indicators and developing drought impact models.

Only very few studies to date have exploited text-based impact datasets. Dieker at al. (2010) qualitatively and quantitatively compared the USDM to impact data from the US DIR. Stagge et al. (2014) and Blauhut et al. (2015) both worked with EDII data at the country- or macroregion-scale across Europe, with impacts coded as a binary response variable (impact versus no impact) to determine the likelihood of impact occurrence for different impact types. Bachmair et al. (2015) also used EDII data to test the feasibility of evaluating drought indicators with impacts at smaller spatial scales in Germany. As an extension to Stagge et al. (2014) and Blauhut et al. (2015), they replaced the binary data with the number of impact occurrences, thus providing a measure of impact severity. A correlation analysis and extraction of indicator values concurrent with past impact onset showed variability in indicator performance and onset thresholds at the sub-country scale and between drought events. The effect of different impact categories or types was not assessed (Bachmair et al., 2015).

Building on these previous efforts, the aim of this study is to exploit the EDII to link drought indicators to impacts using quantitative methodologies. Germany (DE) and the UK were selected as a test-bed, since they represent the countries with most impact data in the EDII database, but the aim is to develop methods that can be extended to other geographical areas in future applications. Specifically, the aims are to

- evaluate different drought indicators using text-based impact information to identify indicators that are meaningful for region-, sector-, and season-specific impact occurrence,
- to empirically determine indicator thresholds representative for impact occurrence, as an alternative to using the default, arbitrarily selected hazard class thresholds intrinsic to indicators such as the SPI,
- to model impact occurrence via machine learning to assess the potential for predictive purposes (i.e. predicting impacts based on indicators alone), and exploit the relationships between indicators and text-based impact data to "backwards learn" about the nature of the impact data itself.

2 Data

2.1 Spatial and temporal resolution

As temporal and spatial resolution of the drought indicator and impact data we selected monthly time series for the period 1970-2012, aggregated at the NUTS1 level (level 1 of the Nomenclature of Units for Territorial Statistics, a spatial unit used in the European Union).

NUTS1 regions represent major socio-economic regions. ~~In Germany they~~This level of spatial aggregation was chosen because of a lack of sufficient data for analysis with finer-scale resolution. However, studies have shown that drought signals typically cover areas larger than NUTS1 regions (e.g. Hannaford et al. (2011)). In Germany NUTS1 regions correspond to the federal states. In the UK there are 12 NUTS1 regions, in Germany 16 (see Table 1 for a list of NUTS1 regions considered for analysis and abbreviations used in this study~~).~~, and Figure 1 for the size of NUTS1 regions). Note that two NUTS1 regions in the UK and three in Germany were excluded from the analysis due to having insufficient impact data (see section 2.3 for details).

2.2 Drought indicators

As drought indicators we selected the Standardized Precipitation Index (SPI) (McKee et al., 1993), the Standardized Precipitation Evaporation Index (SPEI) (Vicente-Serrano et al., 2010), and streamflow percentiles (Q). In addition, groundwater level percentiles (G) were included for Germany. For the SPI and SPEI, accumulation periods of 1-8, 12, and 24 months were chosen. Gridded SPI and SPEI data were calculated based on E-OBS gridded data (version 9.0; 0.25° regular spatial grid (Haylock et al., 2008)) using the R Package 'SCI' (Stagge et al., ~~2015).~~2014). For the UK and Germany the underlying station density of the gridded data is relatively high within Europe, and the dataset is based on more European observing stations than in other European or global datasets (Haylock et al., 2008). The gamma distribution was used for the computation of the SPIs and the generalized logistic distribution for the SPEIs (reference period: 1971-2010). Potential evapotranspiration for the SPEI was estimated using the Hargreaves method (Hargreaves, 1994). For each NUTS1 region, regional averages of mean monthly SPI-n or SPEI-n were calculated. Here, n denotes the accumulation period. The mean was chosen since Bachmair et al. (2015) found little differences between the performance of different indicator metrics per spatial unit (e.g. mean vs. minimum, or 10th percentile vs. percent area with SPI or SPEI below a threshold). The reference period for calculation of streamflow percentiles is 1960-2012 in the UK, and 1970-2011 in Germany (also for groundwater).

The monthly streamflow percentiles are based on monthly mean streamflows. In Germany these are calculated from daily streamflow records for several gauging stations per federal state; monthly groundwater percentiles come from weekly to monthly readings of groundwater levels or spring discharge for several monitoring stations per state (data provision by different agencies of the German federal states, see Kohn et al. (2014)). Many of these stations are used for the federal states' hydrological forecasting systems and thus represent stations with good data quality. Monthly streamflow records for the UK were taken from daily river flow records held on the UK National River Flow Archive (NRFA) (~~www~~http://nrfa.ceh.ac.uk~~/data/nrfa/index.html).~~/). The UK Benchmark Network (Bradford and Marsh, 2003) of near-natural catchments was used, alongside the network of sites used in the National Hydrological Monitoring Programme (NHMP: http://~~www~~nrfa.ceh.ac.uk/~~data/nrfa/~~nhmp~~/nhmp.html~~). No groundwater measurements were used from the UK due to the limited number of NHMP borehole records available in many NUTS regions, reflecting the concentration of productive aquifers in the south and east of the country.

The streamflow gauging stations in the UK and Germany encompass both near-natural and anthropogenically influenced ~~catchments~~streamflow records. Figure 1 displays the spatial location of Q and G measurement stations and the boundaries of the NUTS1 regions in the UK and Germany. The number of stations per NUTS1 region is displayed in Table 1. Regional average mean monthly Q and G values were calculated for each NUTS1 region, provided there was at least one station with non-missing observations in the region. As further predictors that may modify the drought indicators' power to explain drought impact occurrence we also selected the month of impact occurrence (M) and the year of impact occurrence (Y). For this purpose the series of months (1-12) was transformed into a sinusoidal curve shifted by four months (peak in July and lowest value in January).

2.3 Drought impacts

Drought impact data come from the European Drought Impact report Inventory (EDII) (Stahl et al., ~~2012~~2015a), which can be viewed online at http://www.geo.uio.no/edc/droughtdb/ (data extraction for this study: October 2014). The EDII defines a "drought impact" as a negative environmental, economic or social effect experienced under drought conditions. Examples of drought impacts are crop losses, water supply shortages and hosepipe bans, increased mortality of aquatic species, reduced production at thermal or nuclear power plants due to a lack of cooling water, or impaired navigability of streams, to name a few. Drought conditions themselves (anomaly in precipitation, soil moisture, streamflow, groundwater levels etc.), without a negative consequence or at least evoking serious concerns, are not considered an impact. The source of EDII entries is text-based reports on drought impacts, e.g. governmental or NGO reports, books, newspapers, digital media or scientific papers. Each impact report in the EDII contains the following information: 1) a spatial reference (different levels of geographical regionalization, including the European Union NUTS regions standard), 2) a temporal reference (at least the year of occurrence), and 3) an assigned impact category. The 15 categories, e.g. agriculture, water supply, etc., are shown in Figure 2. Each category subsumes several impact type subcategories (see Stahl et al. (~~2012~~2015a) for details).

For the analysis the qualitative information on drought impacts was transformed into monthly time series of number of drought impact occurrences per NUTS1 region. The same methodology as in Bachmair et al. (2015) was applied during the conversion of a “drought impact report” (EDII entry) into “drought impact occurrence” (hereafter termed I). In short, this entails the following (see Bachmair et al. (2015) for details):

- Each impact report was assigned to a NUTS1 region. Impact reports with country-level information only were omitted from the analysis. An impact report was converted into several I if 1) the impact report stated impact occurrence in several NUTS1 regions or 2) an impact fell into several impact subtypes.
- Each I is temporally referenced by specifying a start and end month. Impact reports only stating the year of occurrence were omitted from the analysis. In case only the season was provided in the report, we assumed the drought impact occurred during each month of this season (winter= DJF, spring= MAM, summer= JJA, fall= SON).

For each NUTS1 region and month the total number of I was determined, hereafter termed N_I. Table 1 shows the N_I per NUTS1 region included in the analysis, which sum up to 4551 N_I (UK) and 1534 N_I (DE) in total for each country. Some analyses were undertaken for impacts separated into the 15 impact categories. However, a different kind of split of the data was also made, into two larger groups:

- hydrological drought impacts (I_h), i.e. impacts resulting from drought conditions of surface waters or groundwater,
- impacts due to other types of drought (I_o), i.e. impacts associated with meteorological and soil moisture drought and concurrent extremes (e.g. heat waves).

The differentiation between I_h and I_o is based on a keyword search of the impact description field in the database and therefore does not strictly follow any impact category or impact subtype. Examples of I_h include impaired navigability of streams, increased temperature in surface waters negatively affecting aquatic species, drying up of reservoirs, or reduced fishery production. I_o comprises most agricultural and forestry impacts, impacts on recreation or human health, soil subsidence, or wildfire. Figure 2 shows the total number of I, I_h and I_o per NUTS1 region and season, as well as their categorical distributions.

2.4 Selection of years for analysis

For each NUTS1 region separately, a subset of years within 1970-2012 were selected for analysis based on drought impact occurrence. Years with at least one impact occurrence in the region were selected. All months of the selected years were included in this censored time series. The censoring was undertaken to exclude years with drought conditions yet no impact reports in the EDII, similar to Bachmair et al. (2015). The search for impact reports in both countries focused on known drought events; the absence of impact reports in the EDII for years with drought conditions may therefore be attributable to either a lack of impact occurrence or simply a lack of drought impact reports, whether through not being discovered or not being published in the first place. Table 1 shows the length of time series per region and the percentage of months with impact occurrence in this censored time series. Despite the above-described censoring approach a considerable percentage of months with zero impact occurrence remained. The data analysis was only applied to regions with at least 10 months with impact occurrence, which led to the exclusion of Northern Ireland and Scotland (UK), and the Hanseatic City of Bremen, Hanseatic City of Hamburg, and Thuringia (DE).

3 Methods linking indicators and impacts

3.1 Correlation analysis

First, we carried out a cross-correlation analysis between different drought indicators and the number of impacts, accounting for temporal autocorrelation in the indicator and/or impact time series. Spearman rank correlation coefficients (ρ) were calculated between time series of drought indicators and number of impact occurrences, for each NUTS1 region separately. Rank correlation was chosen over Pearson correlation since the counts of the impact data are not normally distributed. Correlations were undertaken between time series of different indicators on the one hand (mean SPI and SPEI for 1-8, 12, and 24 months; Q; G (DE only); month (M) and year (Y) of impact occurrence), and time series of number of impact occurrences for different impact subsets on the other:

- total impacts (N_I)
- hydrological drought impacts (N_{Ih})
- impacts due to other types of drought (N_{Io})
- impacts per impact category, and
- impacts per season (DJF, MAM, JJA, SON).

A subset of impact data was only included in the analysis if there were at least 10 months with impact occurrence. Since there was temporal autocorrelation present in the time series of SPI and SPEI of longer accumulation periods, in time series of Q and G, and in the impact time series for most UK and some German NUTS1 regions, significance levels of the cross-correlation analysis had to be corrected. Temporal autocorrelation of time series used in cross-correlation analysis violates the assumption of serial independence and increases the likelihood of type I error (Hurlbert, 1984; Jenkins, 2005). We applied the "Modified Chelton method" by Pyper and Peterman (1998), which adjusts the "effective" number of degrees of freedom used for determining significance levels. While we use Spearman's ρ for the cross-correlation analysis, autocorrelation coefficients represent Pearson's r (based on square root transformed data for the counts of impact occurrence). We define strength of correlation as follows: 0-0.1 (no correlation), >0.1-0.3 (weak), >0.3-0.6 (moderate), >0.6-0.9 (strong), and >0.9 (very strong).

3.2 Random forest modeling

Second, we employed a machine learning approach utilizing an ensemble regression tree approach called "random forest" (Breiman, 2001). Similar to the cross-correlation analysis, the random forest approach also identifies drought indicators best linked to impact occurrence. In addition to extracting predictor importance, the random forest approach is used for obtaining splitting values as estimates of thresholds of impact occurrence, and to model drought impact occurrence.

A "random forest" (Breiman, 2001) is a machine learning algorithm, which constructs a large number of classification or regression trees (CARTs) on bootstrapped subsamples of the data.

~~Non-parametric regression using random forest (RF) consists of the following steps (see Liaw and Wiener (2002) for details): 1) n_{tree} bootstrap samples are used. The individual cases making up the sample are drawn randomly with replacement from the original data, preserving each month's pairing of predictand and predictors. The size of each sample is about two-thirds of the size of the total dataset; 2) for each bootstrap sample, an unpruned tree is grown. That is, for each node in turn, a split-in-two of the data is performed for each of m_{try} randomly chosen predictor variables, and the predictor whose split results in the two most homogeneous groups (minimizing the residual sum of squares) of the predictand is chosen as the splitting variable for that node; 3) new data is predicted by averaging predictions over n_{tree} regression trees (Liaw and Wiener, 2002). The user-defined variable n_{tree} was set to 1000. The model parameter m_{try} (number of predictors randomly sampled as candidates at each split) was left as default: one third of the total number of predictors (Liaw and Wiener, 2002). For all other parameters the default was kept as well. The model error is determined by predicting the excluded data ("out-of-bag" data according to Breiman (2001)) at each bootstrap iteration using the tree grown with the bootstrap sample and averaging all errors (Liaw and Wiener, 2002).~~

For our analysis we applied the R package 'randomForest' developed by Liaw and Wiener (2002). Details about the random forest (RF) methodology and model parameterization are given in the appendix. The RF predictors for each NUTS1 region included the same indicators as used in the correlation analysis. The response variable is the square root transformed monthly counts of impact data per NUTS1 region. ~~The transformation yielded a near normal distribution of the non-zero data in many regions. Some British NUTS1 regions, however, showed a bi-modal distribution of NI (NEE, NEW, YHU, and SEE with varying extent), and in some German states the distribution of NI remained positively skewed after the square root transformation. Results for a log-transform were similar.~~ We then ran models for the same subsets of impacts as in the correlation analysis if there were at least 10 months with impact occurrence: total impacts (N_I), hydrological drought impacts (N_{Ih}), non-hydrological drought impacts (N_{Io}), and impacts per impact category.

To identify the drought indicators best linked to impact occurrence we a used the "variable importance" feature of the RF algorithm~~. For each predictor it is assessed by how much the prediction error increases when the "out-of-bag" data for that predictor are permuted while all others are left unchanged (Liaw and Wiener, 2002). We~~ described in Liaw and Wiener (2002), which enabled us to use the ranks of percent decrease in accuracy as variable importance measure (e.g. Strobl et al., 2009). Another output from the RF analysis are the splitting values for each predictor. The construction of each regression tree is based on recursively splitting the data into more homogenous groups (nodes). At each node, the best splitting variable and splitting value are determined, with multiple splits possible for the same variable (Strobl et al., 2009). For our analysis we extracted the splitting values corresponding to each predictor, considering all trees and nodes, and visualized their distribution as boxplot. We regard these splitting values as estimates of thresholds of impact occurrence. All RF models are based on multiple indicators. Therefore, indicator thresholds of individual indicators are conditional on predictor interactions.

The predictive potential of the random forest models was assessed in two ways. First, the overall model performance was evaluated based on a 10-fold cross-validation. The goal of this assessment (hereafter “RF Predictions”) is to test the performance of RF models as a potential tool for predictive purposes, and to learn about the indicator-impact relationship. The data for cross-validation is the censored time series for each NUTS1 region, i.e. the time series based on the sub-selection of years with drought impact occurrence within 1970-2012. For each of the ten model runs the censored time series was split into 90% for training and 10% for prediction; impact occurrence of the left-out 10% is predicted with a random forest model constructed on the training data. The cross-validation procedure allows evaluation of the predictive performance for “unseen” data excluded from model fitting. As model performance metrics we computed mean absolute error (MAE), root mean squared error (RMSE), and error components according to the Kling-Gupta-Efficiency (Gupta et al., 2009) modified by Gudmundsson (2012): relative difference in mean ($\Delta\mu$), relative difference in standard deviation ($\Delta\sigma$), and strength of correlation between observed versus modeled number of impacts (r). Zero is the optimal value of $\Delta\mu$ and $\Delta\sigma$; negative and positive values indicate under- and over-prediction, respectively (Gudmundsson et al., 2012).

The second assessment (hereafter “RF Backwards Learning”) is the application of the RF models that were fitted to the censored time series to predict N_I per NUTS1 region to those years that had been excluded, i.e. the years within 1970-2012 that have zero impact occurrence. The purpose of this second assessment is to scrutinize the impact data in the EDII database to backwards learn where a year without impacts may either be due to no impacts or due to the lack of reporting or finding reports. As the observations themselves are examined no model performance metrics are presented.

4 Results

4.1 Correlation of indicators with impacts

In the UK the strength of correlation between times series of N_I and different indicators ranges between -0.65 and 0.51 (Figure 3). Lower indicator values coincide with higher N_I (negative correlation) for all drought indicators except for M, where positive values in summer concur with a higher N_I (positive correlation). Overall, SPI and SPEI are very similar in terms of strength of correlation. For southern and central UK, accumulation periods of SPI and SPEI exceeding about 6 months show the strongest correlation with N_I, whereas the more northern regions show the strongest correlation for short to intermediate accumulation periods. SPI-24 and SPEI-24 are the indicators with the strongest correlation for half of the NUTS1 regions (WAL, CWE, EE, SWE, and SEE), with ρ ranging between -0.38 and -0.65. Streamflow percentiles display a moderate and significant ρ in parts of eastern England~~: SEE (-0.46), EE (-0.47), and CEE (-0.32). For~~, but for the other regions the correlation is weak to moderate and not significant at the 5% level (two-sided test). There is mainly no or a weak (non-significant) correlation with Y, which varies in sign.

A split into I_h versus I_o, and a split by impact category reveal distinct differences in correlation patterns for some impact subsets (Figure 3). The difference between I and I_h is rather minor. As can be seen in Figure 2, I_h is the dominant impact type in the UK. Other drought impacts (I_o) show a distinctly different pattern. With weak to moderate ρ for all indicators, no best SPI and SPEI time scale can be singled out. For agriculture, which mostly represents I_o, only CEE and CWE show strong relationships, but for all accumulation periods. While the correlation patterns for water supply and freshwater ecosystem impacts are similar to I_h, shorter to intermediate accumulation periods of SPI and SPEI (4 to 8 months, for a few cases also 12 months) show highest correlation with water quality impacts. For other impact categories correlation could only be determined for very few regions (wildfire, tourism, waterborne transportation), or not at all due to too few months with impact occurrence.

A split by season (Figure 4) also shows distinct differences, yet could not be determined for all regions given limited impact data if partitioned seasonally. ~~In winter and spring the general trend stays the same as for the full series (higher ρ for longer accumulation periods of SPI and SPEI, 12 and 24 months dominating). In the fall, in contrast, there is a notable shift towards intermediate SPI and SPEI time scales as best indicators in many regions. In summer, the correlation pattern is more diverse, but in general is dominated by strong correlations across the majority of indicators and accumulation periods. Also, the correlation with streamflow percentiles in summer is higher and more often significant when compared with year-round data.~~

In Germany, the overall strength of correlation between times series of N_I and different indicators is in a similar range as in the UK (-0.62 to 0.74). Contrary to the UK, shorter to intermediate accumulation periods of SPI and SPEI best correlate with impact occurrence (Figure 5). Eleven of the 13 analyzed regions show the highest ρ for SPEI-2 to SPEI-4; for SPI-24 and SPEI-24 a non-significant correlation in inverse direction is found. The difference between SPI and SPEI is slightly more pronounced in Germany, with SPEI performing somewhat better (absolute difference in ρ up to 0.13). Q performs similar to SPI in many cases. Groundwater level percentiles show no or non-significant weak correlation with N_I. In contrast, the sine expression of the month shows a higher and often significant ρ, especially in the northern NUTS1 regions. Similar to the UK, there is no or only a weak correlation with Y. As in the UK, there are regional differences, yet mostly regarding the strength of correlation. Most regions in the north and northeast of Germany display a noticeably lower strength of correlation (mostly weak ρ) than the central and southern regions.

Similar to the UK, a split into I_h and I_o reveals differences in correlation patterns compared with I, yet the picture for I_h and I_o is the opposite: while the correlation pattern for N_{Io} is rather similar to N_I, there is a noticeable shift towards higher correlation with longer SPI and SPEI time scales for I_h. N_{Io} dominates over N_{Ih} in some German regions, in contrast to the situation in the UK (Figure 2). ~~For several states the correlation between Q and~~ $\cancel{N_{Ih}}$ ~~is higher than between Q and~~ $\cancel{N_I}$. A further split by impact category uncovered the following: agricultural impacts show highest ρ for SPI and SPEI time scales of 1-4 months, yet most correlations are weak and not significant; there is a shift towards higher correlation with longer SPI and SPEI timescales for impacts on waterborne transportation in some NUTS1 regions; for all other impact categories correlations could only be determined for one or two regions (BV or BW or

RP) due to too little impact data. A seasonal split was also not possible to assess due to too few months with I in spring, fall, and winter; the majority of impacts in Germany occurred in summer (Figure 2).

4.2 Indicator importance in random forest models

For the UK, the general picture from the random forest approach is very similar to the findings from the correlation analysis, both regarding I and different impact subsets (I_h, I_o, and I per impact category) (Figure 6). Long accumulation periods of SPI and SPEI (12 and 24 months) appear as the highest ranking predictors for most regions, except the more northern regions NEE, NEW and YHU. Q does not show up as important predictor. Distinct differences compared with the correlation analysis include the following: 1) Y plays an important role for I and most impact subsets; 2) for I_o, the RF predictor importance shows a shift to intermediate accumulation periods of SPI and SPEI (7/8 months). This shift is not as clearly discernible in the correlation patterns. The same holds true for the agricultural impacts.

In contrast to the UK, where the RF predictor importance plots look very similar to the correlation analysis plots, there is more variation for Germany (Figure 7). The RF predictor importance patterns are spottier than the correlation analysis patterns with less smooth transitions between adjacent indicators. Nevertheless, the general tendency of best predictors is confirmed. ~~Short to intermediate accumulation periods of SPI and SPEI are highest ranking predictors; the sine expression of the month is top-scoring in the northern states for I, I_o, and agricultural impacts. Also, there is a shift towards higher correlation with longer SPEI accumulation periods (7/8 months) for I_h and impacts on waterborne transportation. Y shows lower importance than for RF models of UK regions.~~

4.3 Indicator thresholds in random forest models

While splitting values of all indicators for all impact subsets (I, I_h, I_o, different impact categories) were extracted, we only show the threshold distribution, i.e. splitting value distribution, for selected SPI and SPEI time scales ~~of 8, 12, and 24 months~~ (best performance for different regions and/or impact subsets) and streamflow and groundwater level percentiles (Figures 8 and 9). While we display the threshold distribution of individual indicators, it is important to remember they are conditional on multi-predictor interactions in the RF model.

For the UK, the threshold distribution for both meteorological indicators generally shows a considerable range, which decreases with increasing accumulation period~~ (roughly +2 to -2.5/-3.5 for SPI-8, +1.5 to -2.5/-3 for SPI-12, and +1 to -2.5 for SPI-24).~~. For the same accumulation periods of SPEI the range extends to less negative values. Apart from this, the differences between SPI and SPEI are negligible with interquartile ranges (IQR) predominantly between 0 and -2. When only focusing on the median of the distribution, SPI-8 and SPEI-8 values scatter around -1 for most NUTS1 regions. For SPI and SPEI of 12 and especially 24 months duration the scatter around -1 is slightly more variable~~, and differences among NUTS1 regions are somewhat stronger.~~. Regarding streamflow percentiles the splitting values cover almost the entire range, the IQR is distinctly larger than for SPI and SPEI, and the median ranges between 0.2 and 0.37. The split by impact category results in slightly narrower ranges of threshold distributions for many impact categories, and often a more negative median (not shown). ~~This is not the case for I_h and water supply impacts; yet, there is much variation among indicators.~~ All indicators show regional differences, however without systematic patterns.

~~For Germany, SPI and SPEI of 3 and 6 months accumulation period are generally well linked to N_I or impact numbers in different impact subsets. Figure 9 shows that~~For Germany, the splitting values in the different federal states range from roughly +1.5 to -2/-3 for both SPI and SPEI~~.~~ (Figure 9). Absolute values of the IQR of German regions are similar to the UK. Contrary to the UK, a regional pattern exists regarding the median of the SPI and SPEI threshold distributions. The southern and most central federal states display a more negative median (mainly between -1 and -1.5) than the northern/northeastern states (with a median between 0 and -1). A small but noticeable gradient from SH to BV can be seen in Figure 9. ~~A further difference to the UK is the more pronounced differences between SPI and SPEI thresholds, with more negative threshold values for SPEI.~~ Streamflow percentiles show a similarly large spread of splitting values to the UK, yet the IQR is mostly smaller and the median is slightly lower (0.14-0.29). ~~Regional differences occur as well, but, similar to the situation for SPI and SPEI, these differences are less pronounced in Germany than in the UK. No pattern is found for~~For groundwater level percentiles~~. The~~, the median per region ranges between 0.2 and 0.68~~. The split by impact category often resulted in less negative splitting values for I_o and agricultural impacts compared with I_h (not shown). Too little~~; no regional pattern is found. The low amount of impact data for the RF analysis for several impact categories prevented a systematic intercomparison among impact categories.

4.4 Impact predictions with random forest models

RF Predictions for the UK show that observed and modeled impacts agree well for the NUTS1 regions SWE, SEE, and EE (Figure 10). In most central regions and LND there is more spread. The northern regions NEE and NEW show least agreement. The R^2 ranges between 0.16 (NWE) and 0.73 (WAL) (Table 2). Due to the random component in the RF algorithm, model performance varies marginally for replications. Regional differences more or less reflect the length of each time series and the percentage of months with impact occurrence. That is, regions with $R^2 > 0.6$ generally have longer time series and a higher percentage of months with I than regions with lower R^2 (Tables 1 and 2). For Germany, observed and modeled impacts agree less well than for many UK regions (Table 2). However, much fewer data points for Germany than for the UK make a comparison difficult (Figures 10 and 11). Among the federal states of Germany, BV and BB show better agreement than other regions. The majority of federal states ~~shows~~yielded an R^2 between 0.33 and 0.54 (Table 2). Only four states show an $R^2 > 0.6$. Overall, the lower agreement between observations and predictions than in the UK concurs with the shorter time series of indicator and impact time series in Germany, and a smaller percentage of months with $N_I > 0$ (Table 1).

The generally small difference in the mean ($\Delta\mu$) of observed versus modeled impacts for both the UK and Germany (Table 2) suggests that the central tendency is well modeled. However, a closer look at the time series of observed and modeled number of impact occurrences (Figure 12, time series with gray background (RF Predictions)) reveals that small values are generally over-predicted and large values often under-predicted. ~~Notable under-predictions of peak values include, for example, events in 2003 in Germany, and in 2011/12 for many regions in the UK.~~ The under-prediction of N_I causes lower standard deviations for the modelled values than for the observed ($\Delta\sigma$ between -0.22 and -0.52, see Table 2).

Furthermore, Figure 12 shows that predictions and observations in the UK and Germany generally agree well both regarding initiation of impact occurrence and its subsequent temporal evolution. This is also reflected by a moderate to strong correlation between predictions and observations (Table 2). The blue line in Figure 12 represents an impact threshold of one, as guidance for interpretation: modeled impacts smaller than one may be regarded as an absence of impacts. Taking this into account the temporal dynamics agree even better, especially regarding impact onset. An obvious disagreement between dynamics of observations and predictions is found in many regions in the UK in 1991/1992, where modeled N_I is more dynamic than the observed static "block" of N_I following an impact peak. The block-shaped data represent impacts due to a contraction of the stream network in large parts of the south and east of the UK during these years. In Germany, states with larger amplitude of N_I (BV, BW, RP, and NW) tend to have a better agreement of temporal dynamics, especially when only focusing on values above the one-impact-threshold line. For states with low amplitude of N_I, which often concurs with less negative splitting values (see section 4.3), the temporal dynamics are less well modeled (not shown).

The RF Backwards Learning predictions for all years with zero impact occurrence according to the EDII database are shown on white background in Figure 12. They expose instances of potentially "false-positive impacts", i.e. a positive number of impacts is modeled while there are no observed impacts. A clear example for the UK is the period 1972-74, when drought conditions occurred, which would have caused impacts in many UK regions according to the RF model trained on the censored time series. Another example of false-positive impacts in the UK is found for many southern and central regions in the second half of the 1990s after a peak of N_I in 1995. While for the UK two major, spatially coherent cases of false-positive impacts exist, the pattern for Germany is more diverse and region-specific. ~~In BW, for instance, the impact data in the EDII appears to well represent true impact occurrence (no significant false-positive impacts). IN BV and BB, in contrast, false-positive impact events are noticeable in 1971/1972 (BV) and 1976 (BB; not shown). During these periods drought impacts are present in the EDII for other states in the vicinity. Remarkable as well is that states with low amplitude of~~ $\cancel{N_I}$ ~~and less negative splitting values (see section 4.3) are characterized through frequent false-positive impacts with small~~ $\cancel{N_I}$ ~~(e.g. LS, not shown).~~

5 Discussion

5.1 Performance of drought indicators

The correlation analysis and the random forest approach revealed the following insights about the performance of drought indicators, which will be discussed in the context of expectations and literature: 1) the best-performing drought indicators are region and impact category specific, and in the UK season specific to some degree. While in the UK generally long accumulation periods of SPI and SPEI (12-24 months) performed best, short to intermediate accumulation periods (2-4 months) were best linked with drought impacts in Germany. However, there is spatial variability within each country, and differences among impact categories. 2) A comparison among indicators (SPI vs. SPEI vs. Q (vs. G in Germany)) uncovered that in the UK SPI and SPEI perform similarly to each other, and Q performs less well. In Germany SPEI often performed slightly better than SPI, the linkage with Q is better than in the UK, and there is low agreement between G and impact occurrence. 3) The largely congruent findings from the two different statistical approaches independently validate the results.

While much can be speculated about the drivers of region-, impact type-, and season-specific variability, it is nonetheless necessary to explore the underlying mechanisms for the observed differences to rule out purely data-driven, yet physically meaningless, indicator-impact-relationships. Regional differences can result from both 1) “real” physical, spatial differences in geographic properties (e.g. climate, geology, soil, land use), vulnerability towards drought, and hazard characteristics, triggering impacts differing in type and response time, and 2) differences due to inherent spatial and temporal biases in the impact data (see Bachmair et al. (2015) on potential EDII error sources).

In the UK we found differences in best SPI and SPEI accumulation periods between most southern/central regions (long periods) versus more northern regions (shorter periods). This corresponds well to known differences in the nature of the drought hazard, and impacts. Strong regional contrasts in drought occurrence across the UK have been noted previously, with a particular contrast between the upland northern and western UK, which is susceptible to short-term (6 month) summer half-year droughts, and the lowlands of the south-eastern UK that are susceptible to longer-term (18 month or greater) multi-annual droughts (Jones and Lister, 1998; Marsh et al., 2007; Parry et al., 2011). These findings reflect both the climatological rainfall gradient across the UK and the predominance of groundwater dominated catchments in the south-east (Folland et al., 2015). While we also found regional differences in indicator-impact-linkage patterns in Germany, they mostly relate to differences in strength of correlation (weaker correlation in northern/northeastern states). The smaller amplitude of impact time series in these states may explain weaker correlation in contrast to southern/central states with predominantly larger amplitude, i.e. pronounced impact peaks, as hypothesized by Bachmair et al. (2015). ~~In contrast to the UK, which has seen a limited number of multi-annual droughts, most droughts in Germany have been of shorter duration, although such short (typically summer) droughts are fairly frequent. (e.g. Bradford, 2000).~~

The differences in indicator-impact-relationships between the UK and Germany, and some of the within-country variability, are also very likely a result of the regional composition of drought impact types. It is common knowledge that impacts caused by different types of drought have different response times due to propagation through the hydrological cycle (e.g. Mishra and Singh, 2011; National Drought Mitigation Center, 2015; Wilhite and Glantz, 1985). ~~Some impacts develop quickly (e.g. agricultural impacts) during a precipitation shortfall or heatwave and thus show shorter response times than impacts triggered by more slowly evolving streamflow or groundwater drought.~~ In the UK impacts associated with drought conditions of surface waters and groundwater (I_h) clearly dominate (see Figure 2). This agrees well with longer SPI and SPEI accumulation periods as best predictors in the UK compared with Germany. ~~While hydrological drought impacts still make up the larger part of impacts in Germany~~There, the fraction of non-hydrological drought impacts (I_o) is distinctly larger than in the UK. Agricultural and forestry impacts in Germany account for roughly 20-70 percent of impacts depending on the region, and this may explain why short to intermediate SPI and SPEI accumulation periods are the best predictors. ~~In British regions these two impact categories sum up to a maximum of 20 percent. A subdivision of I_h reveals that in the UK impacts on water supply and freshwater ecosystems are most prominent, whereas in Germany impacts on waterborne transportation and water quality dominate in most regions.~~

The identification of best-performing indicators for specific impact types is a key outcome of this study. ~~While the absolute values of best SPI and SPEI accumulation periods were not identical in both countries, we found commonalities in the relative shift from total impacts to different impact types.~~ For instance, agricultural and hydrological drought impacts were generally best linked to shorter and longer SPI and SPEI time scales, respectively. Here, “shorter” and “longer” refers to different absolute values: 1-4 (DE) and 7-8 months (UK) for agriculture, and 7/8 (DE) and 12/24 months (UK) for I_h. Perhaps unsurprisingly, a universal recommendation about best indicators hence cannot be inferred. However, the similar relative shift in best SPI and SPEI time scales suggests that there are likely to be typical patterns of response for given impact types, but that these are mediated by regional cause-effect-mechanisms. This is in line with ~~two~~results of the studies ~~introduced earlier, which investigated likelihood of impact occurrence specific to particular impact types across different European countries (~~by Blauhut et al~~.,~~. (2015~~;~~) and Stagge et al~~.,~~. (2014). Seasonal variation in linkage patterns as observed in our study for the UK further complicates recommendations regarding a single best drought indicator. Part of the variation across the seasons is likely to reflect differences in impact type distribution between the seasons (see Figure 2). For example, the long SPI and SPEI time scales for winter and spring in permeable catchments in the southeastern lowlands (Figure 4) reflect long groundwater droughts, which in turn affects groundwater-fed rivers. The winter half-year is the main recharge season and failure to recharge will trigger water use restrictions, while shrinking headwaters will result in freshwater ecosystem impacts. However, less permeable catchments are likely to respond more readily to winter rainfall as the evapotranspiration is low in this season. For the bulk of rivers, the SPI and SPEI time scales are therefore shorter, with impacts related to low absolute water levels mainly in summer and fall, although effects can be long-lasting.

A surprising result is that streamflow did not appear as an important drought indicator in the UK, even after a separation of hydrological drought impacts. In Germany, groundwater level percentiles played only a minor role. There are several possible reasons for these discrepancies. For groundwater level percentiles the mismatch is likely attributable to a lagged groundwater response (Bachmair et al., 2015~~); cross-correlation for different time lags would be a way to assess if and which delay period is linked to impacts.~~). One probable reason for the lack of relationship between I and Q ~~is~~may be the nature of the spatially aggregated streamflow data, which represents different catchments varying in size and characteristics (including degree of human influence), lumped over a large administrative area, which does not coincide with catchment boundaries. A further reason may be the nature of the EDII data, especially regarding the subdivisions of I_h. While in Germany the fraction of instream impacts of I_h is larger (e.g. impaired navigability of streams, water quality, and reduced power~~ plant~~ production due to a lack of cooling water), water supply impacts dominate I_h in the UK. For groundwater or reservoir-fed water supply systems these impacts are, to a certain extent, disconnected from river flows (the purpose of reservoirs being to smooth out variations in instream water availability).

Overall, despite a rather complex picture in terms of best drought indicator for impact occurrence, the empirical evaluation of drought indicators with text-based impact information proved to be a feasible approach. Given the minor differences in the outcomes of the correlation and the random forest analysis for the UK, both methods appear recommendable. Generally, the strength of the random forest algorithm is that it can handle interactions and nonlinearities among variables, and thus identify non-intuitive relationships (Evans et al., 2011; Hastie et al., 2009). Furthermore, random forests are robust to noise (Breiman, 2001; Hastie et al., 2009), and the bootstrap sampling provides a way to account for the uncertainty of the impact data. Nevertheless, the "black-box" nature of the RF model (Breiman, 2001) may not be as useful when an intuitive method for the choice of best drought indicator is needed (e.g. when working with a wide range of stakeholders from different backgrounds). For Germany, systematic differences in indicator-impact-linkage patterns were easier to perceive in the correlation plots than in the RF predictor importance plots. For large data sets the RF algorithm has the potential to detect relatively complex structures; for small data sets, however, this is unlikely to be the case (Maindonald and Braun, 2006). ~~The generally shorter time series for German regions and stronger zero-inflation of the data may therefore explain the "spottier" pattern of RF predictor importance. The correlation analysis thus yielded more powerful results for Germany. However, this method does not provide further information such as on thresholds of impact occurrence, in contrast to the RF algorithm (see section 4.3). Both approaches therefore complemented each other in our study.~~

5.2 Indicator thresholds for impact occurrence

The analysis of splitting values used in the random forest construction highlighted a large spread. Yet, when focusing on the median there are differences between the countries and among the regions (medians around -1 for SPI and SPEI of different accumulation periods in the UK, and in DE between ca. 0 and -1 (north/northeast) and -1 and -1.5 (southern/central states)), and, to some extent, impact categories.

We regard splitting values during recursive partitioning as estimates of thresholds of impact occurrence because they provide guidance on critical predictor values triggering a consequence. Nevertheless, the uncertainty of the text-based impact data clearly must be taken into account in the search for meaningful thresholds. One cause of the large spread of the threshold distributions is the uncertain timing of actual impact occurrence, especially regarding its termination. ~~First, when only the season was provided in the impact report, the assumption was made that impacts lasted during all months of this season. This may cause a mismatch in cases where drought conditions recede within the course of the season.~~ Second, in the UK there are impacts appearing as "blocks" following an impact peak in 1990. They arise from EDII reports citing long-lasting impacts without an exact known end-point or temporal evolution of the severity of the impact (i.e. low flow anomalies in eastern and southern Britain causing contraction of the stream network and thus impacts on aquatic species reported for the years 1990 to 1992). Third, hosepipe bans and drought orders do not represent direct impacts of drought, but are triggered (and canceled) by an administrative/political decision as an intermediate step. The onset and termination of the impacts they are meant to reflect may therefore be more uncertain than those for other, more direct impacts. ~~We tested this by removing all the drought orders from the database and reanalyzing the data, showing that the SPI-24 and SPEI-24 become less dominant and the strongest correlations are shifted towards slightly shorter accumulation durations.~~ These issues highlight the necessity to separately consider phases of drought development and recovery for drought M&EW (Parry et al., in review; Steinemann and Cavalcanti, 2006).

~~Differences~~Fourth, differences in impact reporting between Germany and the UK also need to be considered. In the UK, a significant proportion of impacts for later droughts (2004-2006 and 2010-2012) were sourced from weekly Drought Management Briefs by the Environment Agency (EA). In Germany there is no continuous information on drought impacts, and no unifying impact reporting scheme exists within the federal state structure. ~~In both countries, reporting mechanisms may put more weight on specific impact categories. For example, the EA Drought Management Briefs have an emphasis on water supply and freshwater ecosystems while for other impact categories such information is sparse, or not routinely published.~~

A reason why we consider tree splitting values as meaningful thresholds of impact occurrence is because Bachmair et al. (2015) found similar threshold patterns for Germany using the same impact data but a different methodological approach based on extracting indicator values concurrent with past impact onset. Both approaches revealed differences in indicator thresholds between northern/northeastern versus southern/central German federal states. These differences were speculated to result from differences in geographic properties and thus different vulnerability to drought (Bachmair et al., 2015). The northern/north-eastern states tend to have more sandy soils with lower water holding capacity than in the south, and lower natural water availability (Bundesamt für Gewässerkunde, 2003; Bundesanstalt für Geowissenschaften und Rohstoffe, 2007). This could explain impact occurrence for less negative SPI and SPEI thresholds. ~~Why we did not find systematic differences in thresholds among British regions despite obvious regional differences in geographic properties is not clear.~~

Despite possible shortcomings of EDII data and the method to derive indicator thresholds, we recommend further efforts to empirically validate indicator thresholds with impact data. ~~The use of~~Drought indicator thresholds ~~to issue~~ informed by impact data may complement and allow comparison with local-scale decision making on drought ~~warnings or to trigger management actions of drought plans~~triggers, which is ~~widespread (Shukla et al., 2011; Steinemann and Cavalcanti, 2006;~~usually based on past hydrological data, stakeholder knowledge and the experience of individuals (e.g. Steinemann, 2014).~~ As pointed out in the introduction section there is no consensus on what a meaningful threshold is.~~ In our study the median of the SPI and SPEI threshold distribution ranged around -1 in the UK, which correspond to the transition between mild and moderate drought according to the SPI classification by McKee (1993). At the same time, the differences in median of the SPI and SPEI threshold distributions for Germany (lower values for SPEI) demonstrate that, despite the standardized nature of such indices, the same thresholds (and corresponding statistical return periods) are not necessarily equally meaningful for drought impact occurrence. To ~~our~~improve that knowledge~~, there are hardly any publicized~~ base, more studies should systematically ~~evaluating~~evaluate and make public the delineation rules of different drought severity classes by using drought impacts (as e.g. Sepulcre-Canto et al., 2012) or by stakeholders' experience (as e.g. Steinemann and Cavalcanti, 2006).~~ Our analysis and previous findings on indicator thresholds for impact onset in Germany (Bachmair et al., 2015) demonstrate the potential of text-based impact data to do this.~~

5.3 Lessons learned from random forest predictions

The two parts of the random forest modeling exercise exposed that: 1) there are differences among regions in terms of predictive power, with RF models for regions with better impact data (longer censored time series, a higher percentage of non-zero data, and larger amplitude of the impact time series) showing good agreement between observations and predictions. 2) While the temporal dynamics of impact occurrence were reasonably reproduced, over- and under-prediction of small and large values, respectively, are an issue. 3) Backwards leaning about impact occurrence for years with no observations (through RF models trained on drought years) provided valuable insights into time periods which potentially lack impact data in the EDII.

Overall, the analysis revealed that RF models generally represent a suitable tool for drought M&EW, yet further model tuning is possible (e.g. reduction of predictors, grouping several regions for increasing the number of observations, and impact category specific models). The finding that there is good agreement between observed and predicted number of drought impact occurrences for regions with good data availability is promising. It~~ also~~ underlines the benefit of spending time and resources on impact data collection. ~~Currently the process of impact data collection is not automated but labor intensive. Good model performance for South West England, for example, which is characterized by better data availability than in other regions, makes a strong argument for the value of impact monitoring.~~ The necessity of expanding impact data collection and its benefit for drought M&EW has also been reported by others (Lackstrom et al., 2013; Stahl et al., ~~2015~~2015b; Wilhite et al., 2007).

Despite the promising predictive capability of RF models for some regions, the under-prediction of peaks is an issue. ~~There are several possible reasons~~One reason for this~~. First, there seems to~~ may be an inherent bias of the random forest algorithm with high values being under-predicted and low values being over-predicted, as observed by others (Ordoyne and Friedl, 2008). This is because the RF algorithm computes averages over a large number of model predictions and hence reduces the range and variance of predictions compared with observed values (Liaw and Wiener, 2002; Ordoyne and Friedl, 2008). ~~Second, there~~Another reason may be an impact-reporting bias caused by impact-reporting increasing during peaks of events. We hypothesize that drought impacts may go unreported during the early stages of a drought, but once a certain threshold of public attention and media coverage is exceeded there is a tendency for more complete reporting. Also, the chances of finding information on drought impacts are higher for recent events due to better online availability of reports and new media channels compared with decades ago. ~~The above described reasons may explain the high number of impacts in the EDII for Germany in 2003 compared with 1976, and the dominance of 2010 - 2012 in the UK. To account for the strong weight of the 2003 drought event, a predictor representing the reporting bias would be needed, which is very difficult to determine or to find proxies for. However, the predictor year may cater for the reporting bias to a certain degree. Another way would be to normalize the number of impacts per drought event but this would distort differences among events. For some UK NUTS1 regions the under-prediction of~~ ~~N_I~~ ~~may also stem from impact reports appearing as static "blocks" following an impact peak in 1990, which was discussed earlier (section 5.2). The modeled time series, which is more dynamic than the observed one, could potentially be more representative of the true impact occurrence (although this is speculative).~~

The RF Backwards Learning assessment provided ~~additional~~a way to scrutinize whether an absence of data in the EDII for certain time periods reflects a true absence of drought impacts, or simply missing data. For the UK, we discovered two prominent examples of ~~where~~droughts that are more severe in modeled impacts ~~are likely to be more representative of the true impact occurrence~~ than ~~the absent impact data in the EDII. For the UK there is an interesting contrast between the false-positive impacts of~~observed EDII impacts: the early 1970s~~,~~ and ~~those of the~~ late 1990s. Both are well documented droughts, but previous studies suggest the former genuinely had less impacts (Cole and Marsh, 2006), in part due to a wet summer in 1973. In contrast, the late 1990s is likely to represent missing impact data. For the 1995-1997 drought, ~~only~~ impacts from the hot, dry summer of 1995 are captured in the EDII~~, as~~; the summer drought had very severe water supply impacts, triggering public enquiries, and was thus very extensively reported~~ due to water supply failures and government responses~~. However, a protracted groundwater drought, with water restrictions in some areas, extended into 1997 (Cole and Marsh, 2006). However no "formal" drought report was ~~written~~ issued on the latter phases of the drought so these ~~later~~ impacts have not been captured by the EDII. ~~Such discrepancies support our choice of time series censoring via drought impact occurrence.~~ Altogether, false-positive impacts identified with the RF Backwards Learning assessment provide guidance on which time periods to focus on when searching for additional impact information. ~~This may, in turn, result in more reliable predictions or impact thresholds based on more drought events.~~

6 ~~Conclusion~~Conclusions

The broad goal of our analysis was two-fold: to learn about the relationship between drought indicators and text-based impact information, to advance drought monitoring and early warning~~,~~ practices; and to test methodologies that can be extended to other locations in ~~a next step.~~future applications. We found that drought indicators best linked to impact occurrence are ~~region~~generally SPI and ~~impact category specific. In~~SPEI with long accumulation periods (12-24 months) for the UK~~ they are additionally season specific~~, and with short to ~~some degree. However, we identified several common traits, allowing~~intermediate accumulation periods (2-4 months) for Germany. Additionally, the ~~potential grouping of regions and/or impact categories according to their indictor~~indicator-impact-response varies within the countries. This calls for evaluating continental drought M&EW systems at smaller spatial scales. Also, our analysis provided additional empirical evidence that impacts associated with different types of drought (e.g. agricultural versus hydrological drought) have different response times, as reflected by distinct differences in indicator-impact-linkage patterns for each impact category. ~~Regarding methodologies~~For regions with sufficient data, a random forest machine learning approach proved to be a suitable tool for objectively identifying indicator thresholds ~~for impact occurrence, and to predict the number of drought impact occurrences for regions with sufficient data. We therefore suggest validating any chosen triggers in drought M&EW with impact data as a complementary approach to, for example,~~of impact occurrence, and for predicting the number of drought impact occurrences. The regression tree splitting values, which we regard as estimates of thresholds of impact occurrence, showed a considerable spread, yet the median revealed differences among regions and, to a lesser extent, impact categories. In the UK the median of threshold values was around -1 for SPI and SPEI. For Germany, distinct differences in threshold values were found between northern/northeastern versus southern/central regions. Such insight into indicator thresholds could provide guidance when designing and validating drought triggers, and complements existing approaches like stakeholder consultation. While there are certainly caveats given the uncertainty in exact timing, number, and severity of impacts, the ~~utilized data~~text-based reports served as a reasonable basis for quantifying impacts. A comparison of time series of observed versus modeled impacts additionally yielded valuable insights into the ~~nature~~contents of the European Drought Impact report Inventory~~ contents~~ and allowed us to identify potential gaps in the temporal coverage of the impact database. Overall, the information gain from evaluating ~~commonly applied~~ drought indicators with impacts underlines the strong benefits of impact data collection, and ~~closes~~is an important step towards closing the gap between knowledge about hazard intensity and on-the-ground drought conditions.

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Appendix

Details about the applied random forest methodology: Non-parametric regression using random forest (RF) consists of the following steps (see Liaw and Wiener (2002) for details): 1) n_{tree} bootstrap samples are used. The individual cases making up the sample are drawn randomly with replacement from the original data, preserving each month's pairing of predictand and predictors. The size of each sample is about two-thirds of the size of the total dataset; 2) for each bootstrap sample, an unpruned tree is grown. That is, for each node in turn, a split-in-two of the data is performed for each of m_{try} randomly chosen predictor variables, and the predictor whose split results in the two most homogeneous groups (minimizing the residual sum of squares) of the predictand is chosen as the splitting variable for that node; 3) new data is predicted by averaging predictions over n_{tree} regression trees (Liaw and Wiener, 2002). The user-defined variable n_{tree} was set to 1000. The model parameter m_{try} (number of predictors randomly sampled as candidates at each split) was left as default: one third of the total number of predictors (Liaw and Wiener, 2002). For all other parameters the default was kept as well. The model error is determined by predicting the excluded data ("out-of-bag" data according to Breiman (2001)) at each bootstrap iteration using the tree grown with the bootstrap sample and averaging all errors (Liaw and Wiener, 2002).

In this study, the response variable is the square root transformed monthly counts of impact data per NUTS1 region. This transformation yielded a near normal distribution of the non-zero data in many regions. Some British NUTS1 regions, however, showed a bi-modal distribution of NI (NEE, NEW, YHU, and SEE with varying extent), and in some German states the distribution of NI remained positively skewed after the square root transformation. Results for a log-transform were similar.

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Table 1. Information on NUTS1 regions in the UK and Germany (DE) considered for analysis

Country	NUTS1 region name	NUTS1 region abbr.	N_I	Length of censored timeseries (months)	Percentage of months with $N_I > 0$	No. streamflow stations	No. groundwater stations
UK	North East	NEE	28	48	22.9	9	-
UK	North West	NWE	400	120	35.8	16	-
UK	Yorkshire and the Humber	YHU	213	108	32.4	11	-
UK	East Midlands	CEE	345	120	37.5	13	-
UK	Wales	WAL	884	156	35.9	20	-
UK	West Midlands	CWE	310	96	42.7	12	-
UK	East of England	EE	545	156	50.0	12	-
UK	South West	SWE	456	156	57.1	23	-
UK	South East	SEE	1079	168	57.1	23	-
UK	London	LND	291	144	45.1	1	-
DE	Schleswig-Holstein	SH	34	60	25.0	9	9
DE	Mecklenburg-Western Pomerania	MP	54	96	28.1	7	4
DE	Lower Saxony	LS	107	132	28.0	38	42
DE	Saxony-Anhalt	ST	46	96	22.9	16	14
DE	Brandenburg	BB	114	96	30.2	21	18
DE	Berlin	BE	57	72	23.6	-	-
DE	North Rhine-Westphalia	NW	143	84	34.5	23	18
DE	Hesse	HE	95	60	43.3	19	18
DE	Saxony	SX	50	96	31.3	23	10
DE	Rhineland-Palatinate	RP	182	84	35.7	20	18
DE	Saarland	SL	42	36	30.6	3	-
DE	Baden-Wuerttemberg	BW	228	84	39.3	28	15
DE	Bavaria	BV	382	72	33.3	69	26

Table 2. Model performance metrics of cross-validated random forest models per NUTS1 region.

Country	NUTS1	MAE	RMSE	$\Delta\mu$	$\Delta\sigma$	r	R^2
UK	NEE	0.44	0.58	0.03	-0.49	0.51	0.26
UK	NWE	1.01	1.48	0.06	-0.51	0.40	0.16
UK	YHU	0.57	0.77	0.00	-0.32	0.76	0.58
UK	CEE	0.72	0.96	-0.01	-0.31	0.74	0.54
UK	WAL	0.82	1.25	-0.01	-0.42	0.85	0.73
UK	CWE	0.59	0.88	0.00	-0.22	0.79	0.62
UK	EE	0.71	0.92	-0.02	-0.40	0.79	0.62
UK	SWE	0.55	0.70	0.01	-0.25	0.84	0.70
UK	SEE	0.92	1.23	0.01	-0.38	0.79	0.62
UK	LND	0.67	0.84	0.02	-0.42	0.67	0.45
DE	SH	0.19	0.31	0.08	-0.25	0.90	0.81
DE	MP	0.35	0.48	0.05	-0.46	0.68	0.46
DE	LS	0.38	0.56	0.04	-0.45	0.73	0.53
DE	ST	0.30	0.45	0.10	-0.40	0.68	0.46
DE	BB	0.43	0.62	-0.02	-0.40	0.78	0.61
DE	BE	0.26	0.50	0.08	-0.30	0.79	0.62
DE	NW	0.57	0.87	0.00	-0.52	0.69	0.48
DE	HE	0.61	0.82	0.08	-0.51	0.61	0.37
DE	SN	0.31	0.43	0.00	-0.41	0.71	0.50
DE	RP	0.68	1.03	0.06	-0.44	0.58	0.34
DE	SL	0.56	0.72	0.13	-0.48	0.65	0.42
DE	BW	0.74	1.16	0.02	-0.32	0.58	0.34
DE	BV	0.68	1.21	0.04	-0.27	0.82	0.67

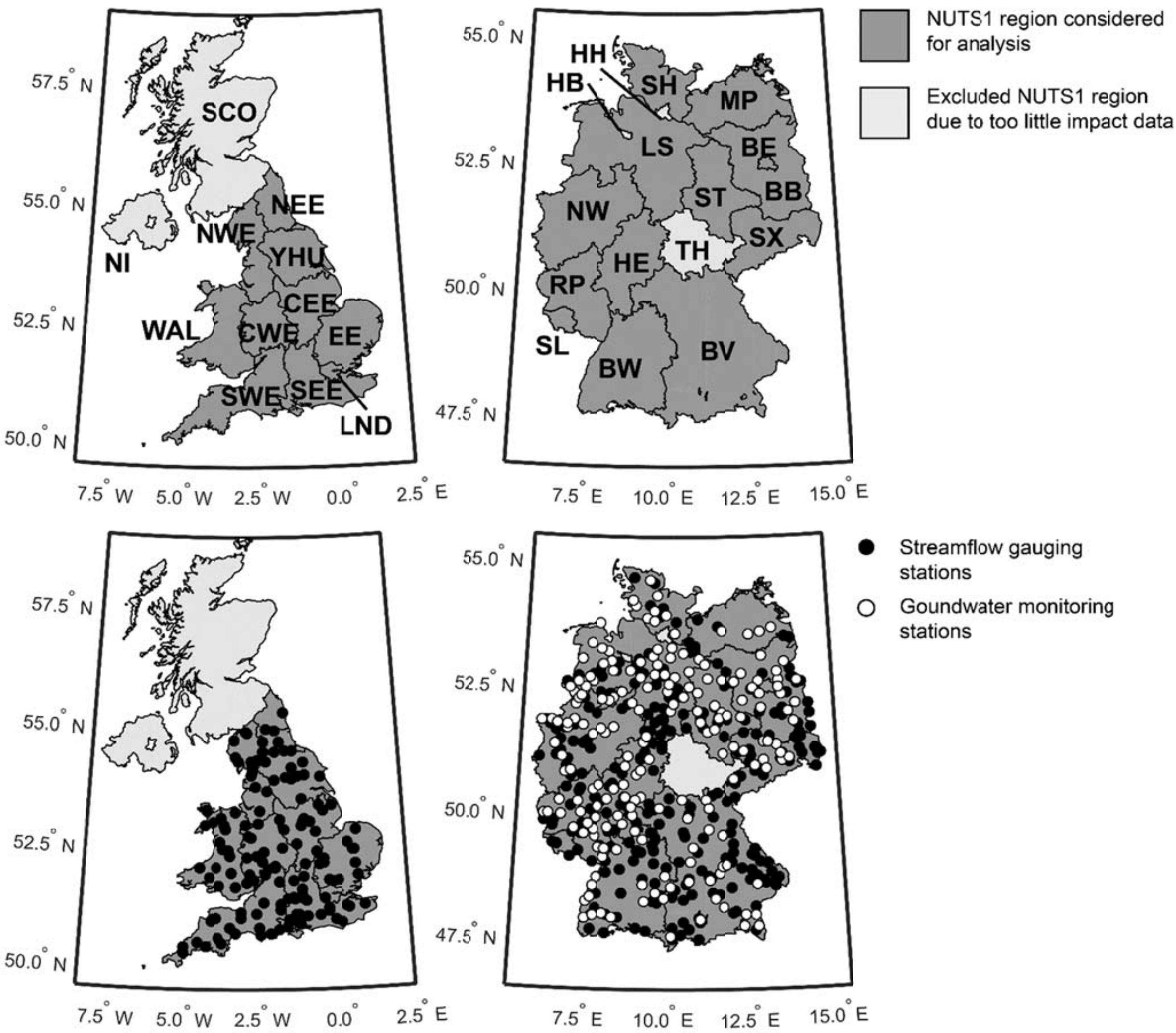
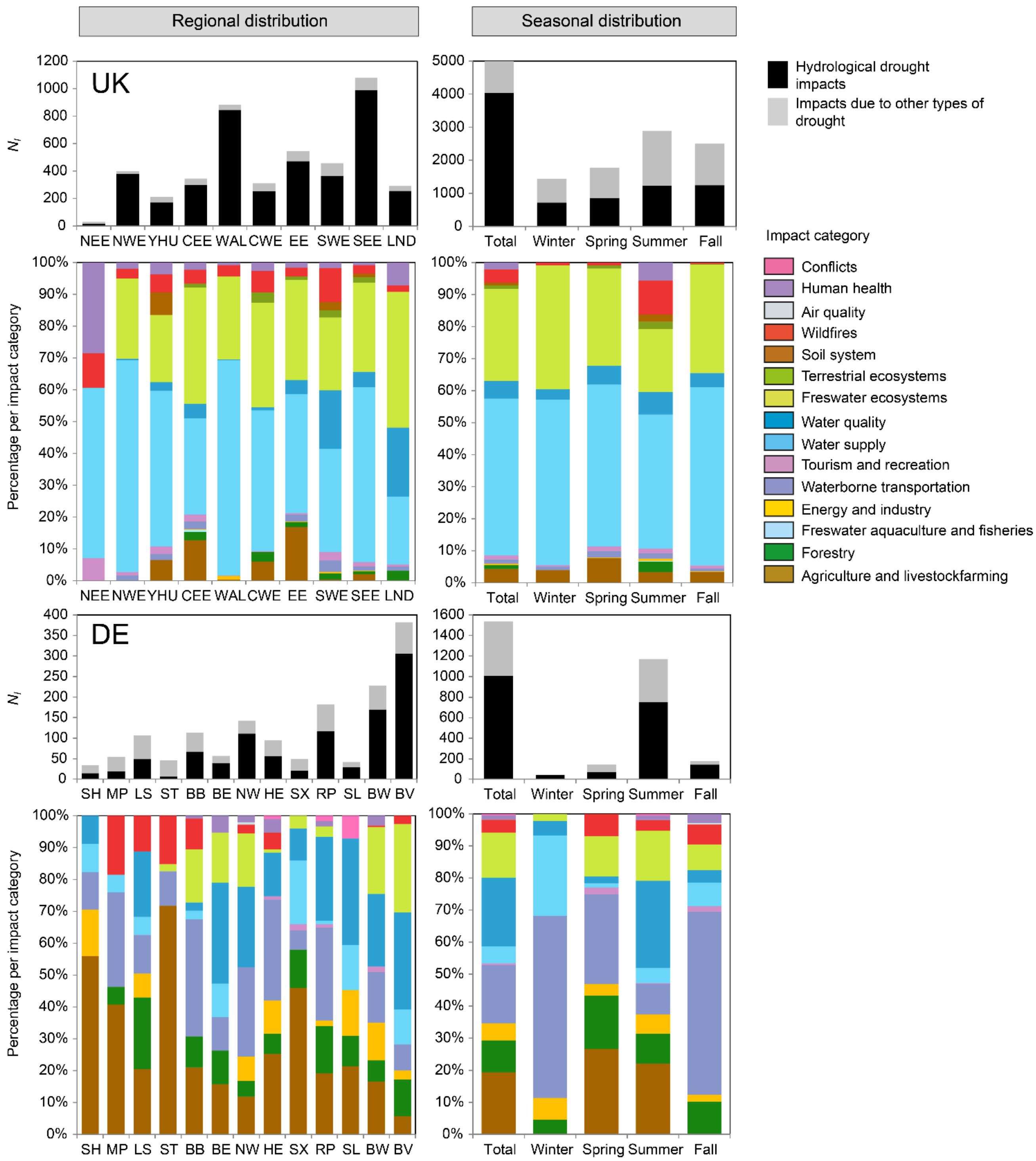


Figure 1: Maps displaying NUTS1 regions in the UK (left) and Germany (right), and the location of streamflow gauging and groundwater monitoring stations. See Table 1 for NUTS1 region abbreviations.



Regional distribution
Seasonal distribution
UK
DE
N_I
Percentage per impact category
NEE NWE YHU CEE WAL CWE EE SWE SEE LND
SH MP LS ST BB BE NW HE SX RP SL BW BV
Total Winter Spring Summer Fall
Hydrological drought impacts
Impacts due to other types of drought
Impact category
Conflicts
Human health
Air quality
Wildfires
Soil system
Terrestrial ecosystems
Freswater ecosystems
Water quality
Water supply
Tourism and recreation
Waterborne transportation
Energy and industry
Freswater aquaculture and fisheries
Forestry
Agriculture and livestockfarming

1

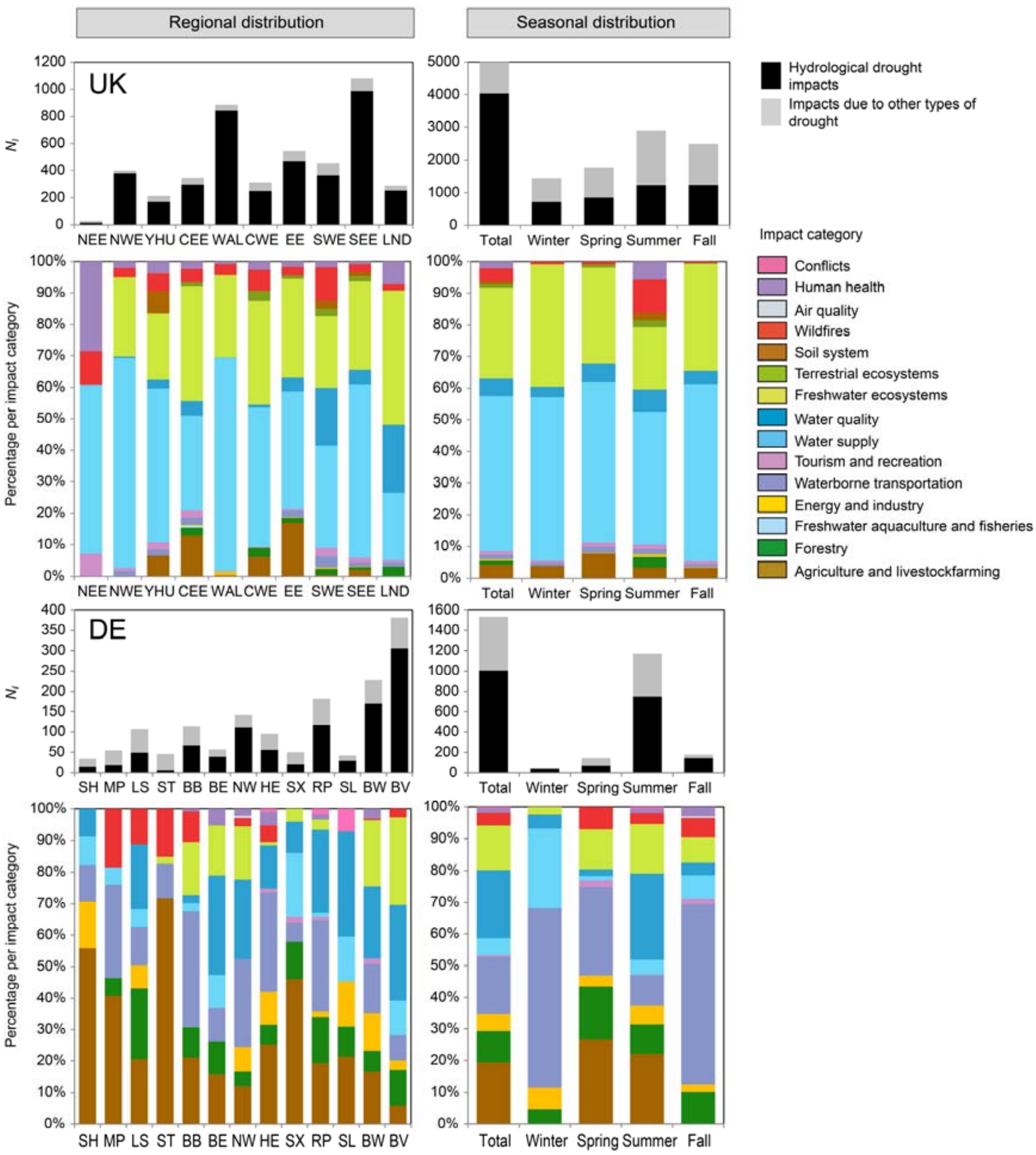
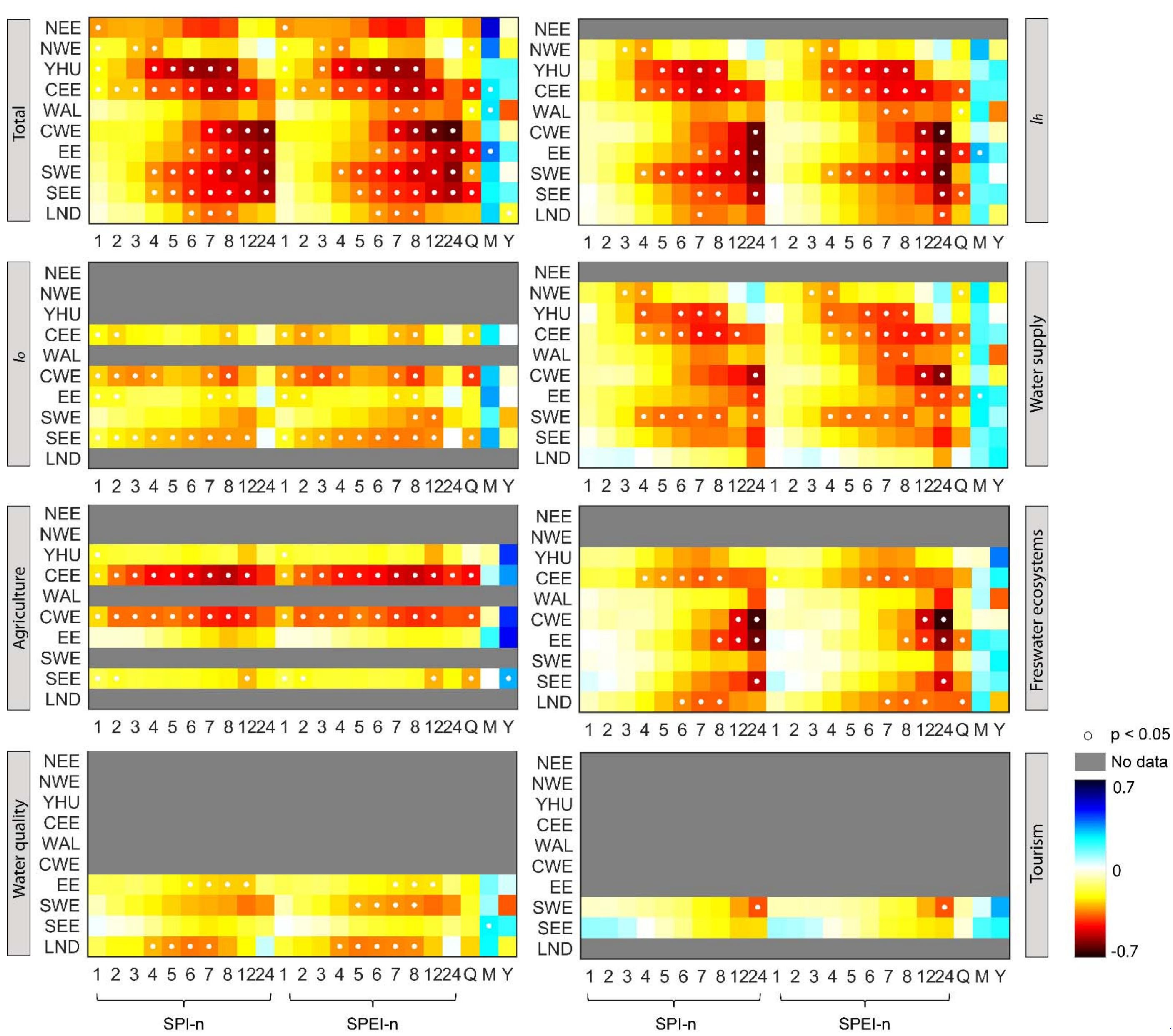


Figure 2: Number of impact occurrences and distribution of impacts per impact category per NUTS1 region and season for the UK (top four plots) and Germany (bottom four plots).

1



Total
Ih
Io
Water supply
Agriculture
Freswater ecosystems
Water quality
Tourism
NEE
NWE
YHU
CEE
WAL
CWE
EE
SWE
SEE
LND
1 2 3 4 5 6 7 8 12 24 1 2 3 4 5 6 7 8 12 24 Q M Y
SPI-n
SPEI-n
p < 0.05
No data
0.7
0
-0.7

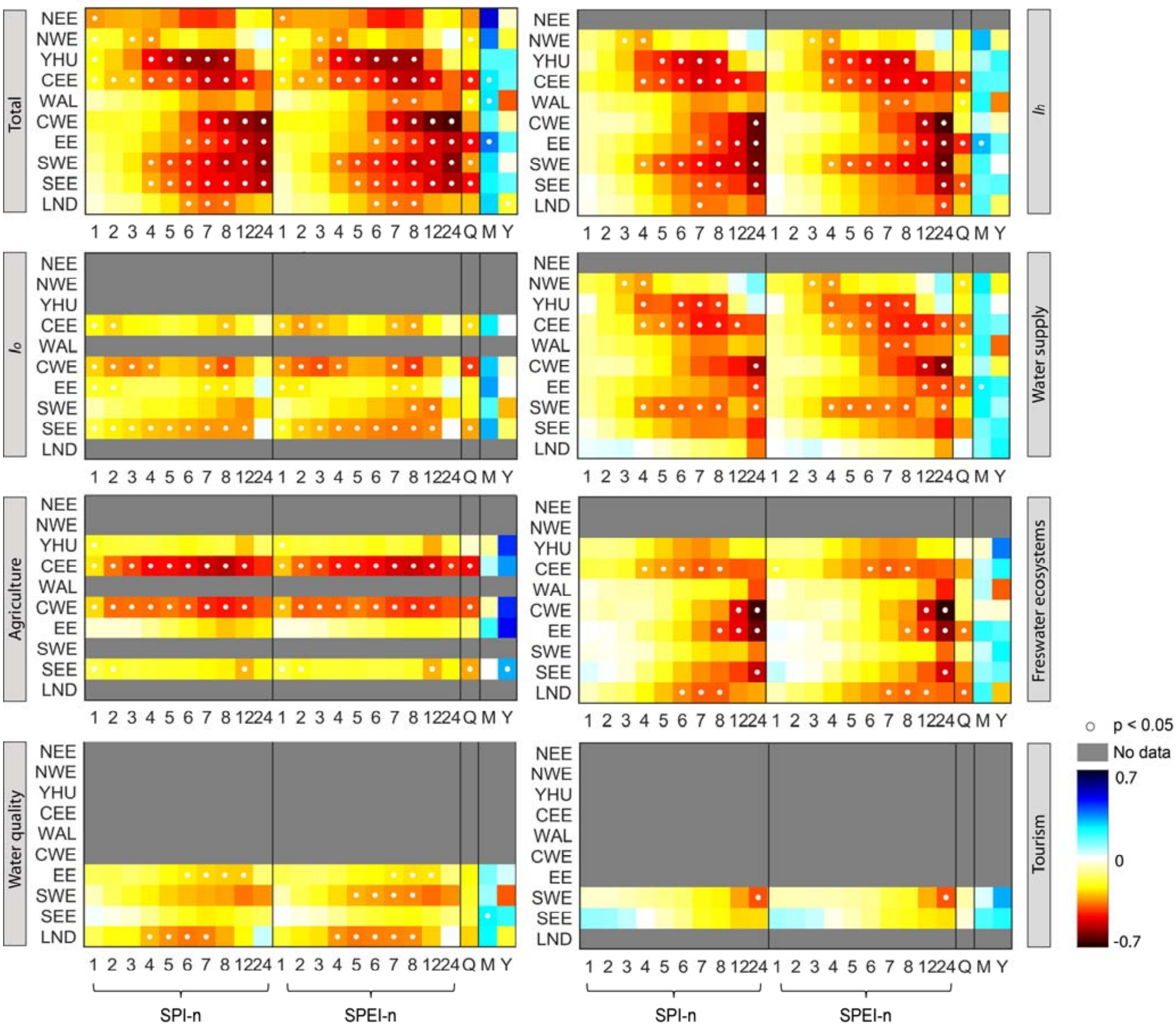
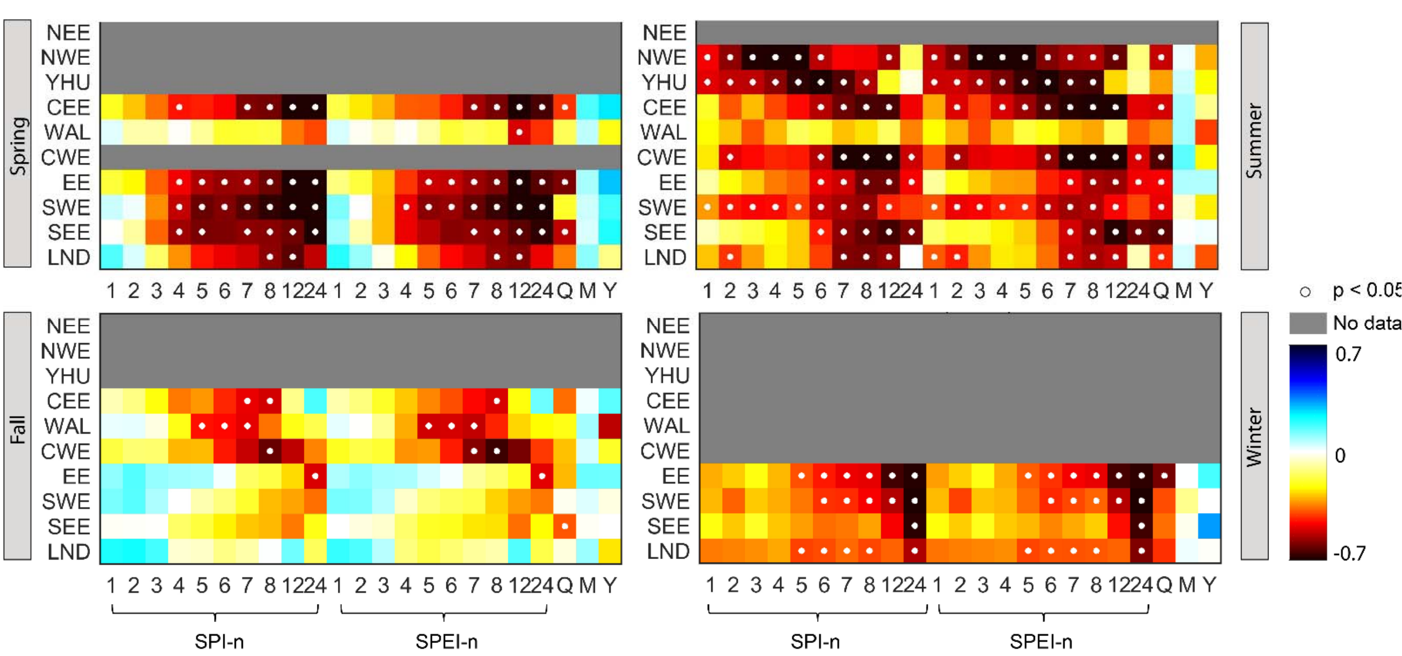


Figure 3: UK: rank correlation coefficients (ρ) between drought indicators and number of impact occurrences for total impacts, hydrological drought impacts (I_h), impacts due to other types of drought (I_o), and selected impact categories per NUTS1 region.



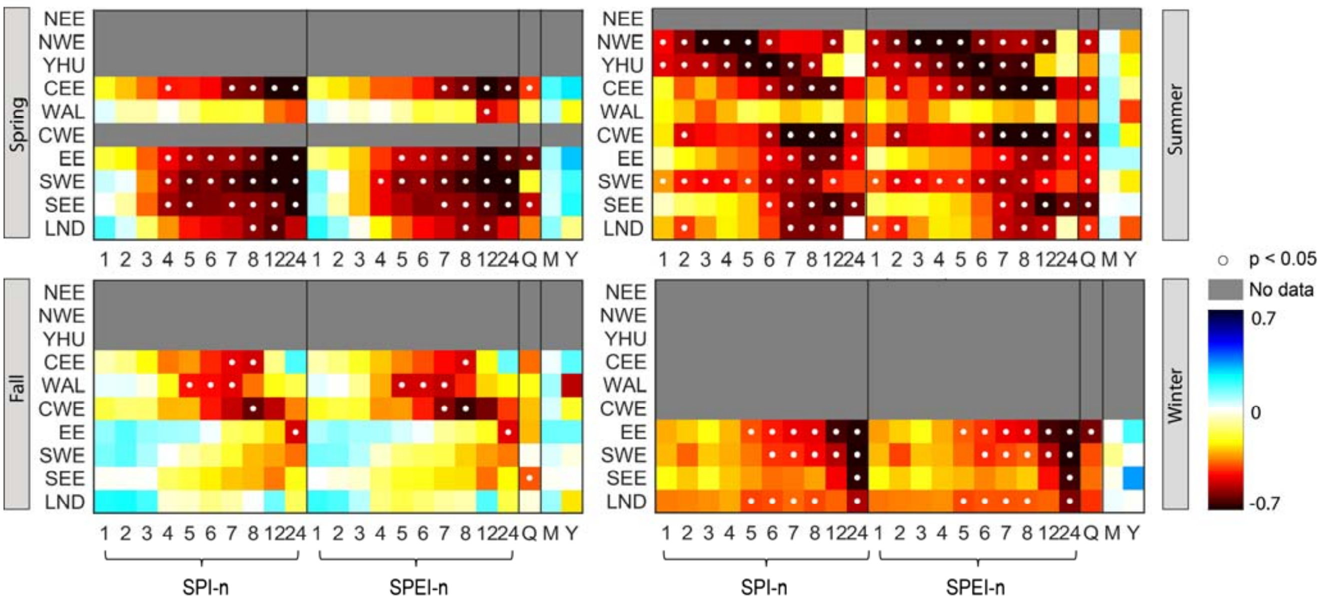
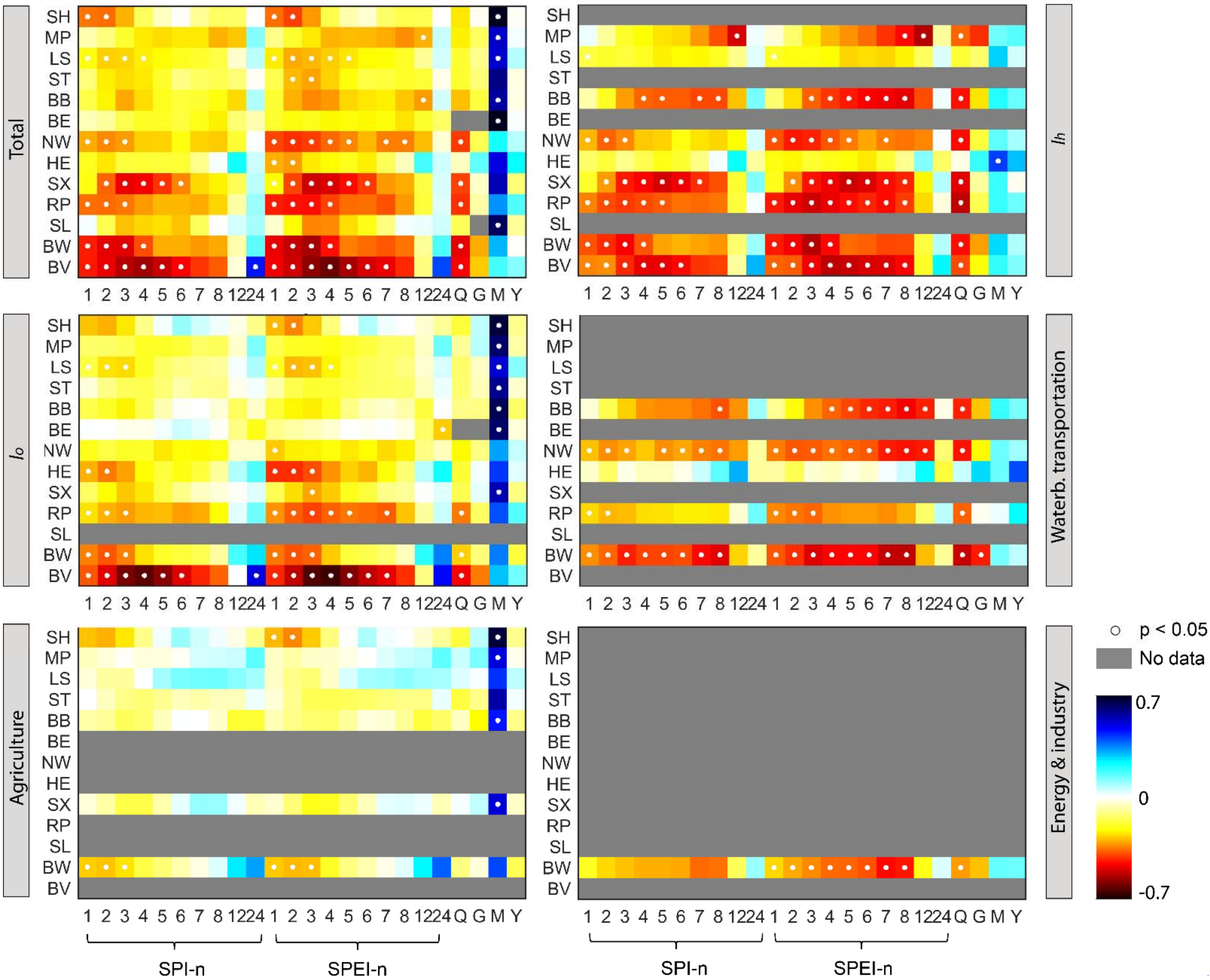


Figure 4: UK: rank correlation coefficients (ρ) between drought indicators and number of impact occurrences per NUTS1 region and season.


Total
I_h
I_o
Waterb. transportation
Agriculture
Energy & industry
SH
MP
LS
ST
BB
BE
NW
HE
SX
RP
SL
BW
BV
1 2 3 4 5 6 7 8 12 24 1 2 3 4 5 6 7 8 12 24 Q G M Y
SPI-n
SPEI-n
p < 0.05
No data
0.7
0
-0.7

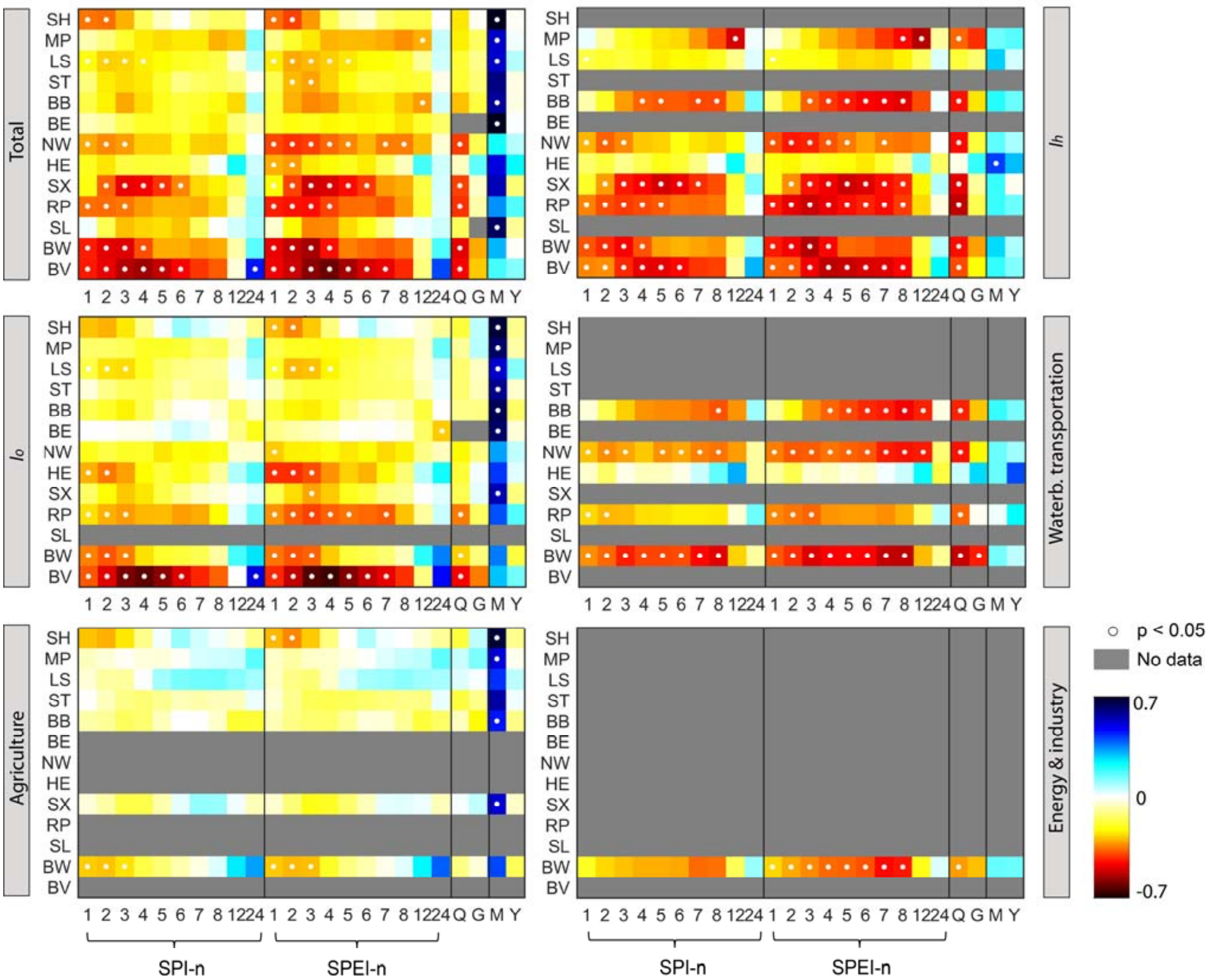
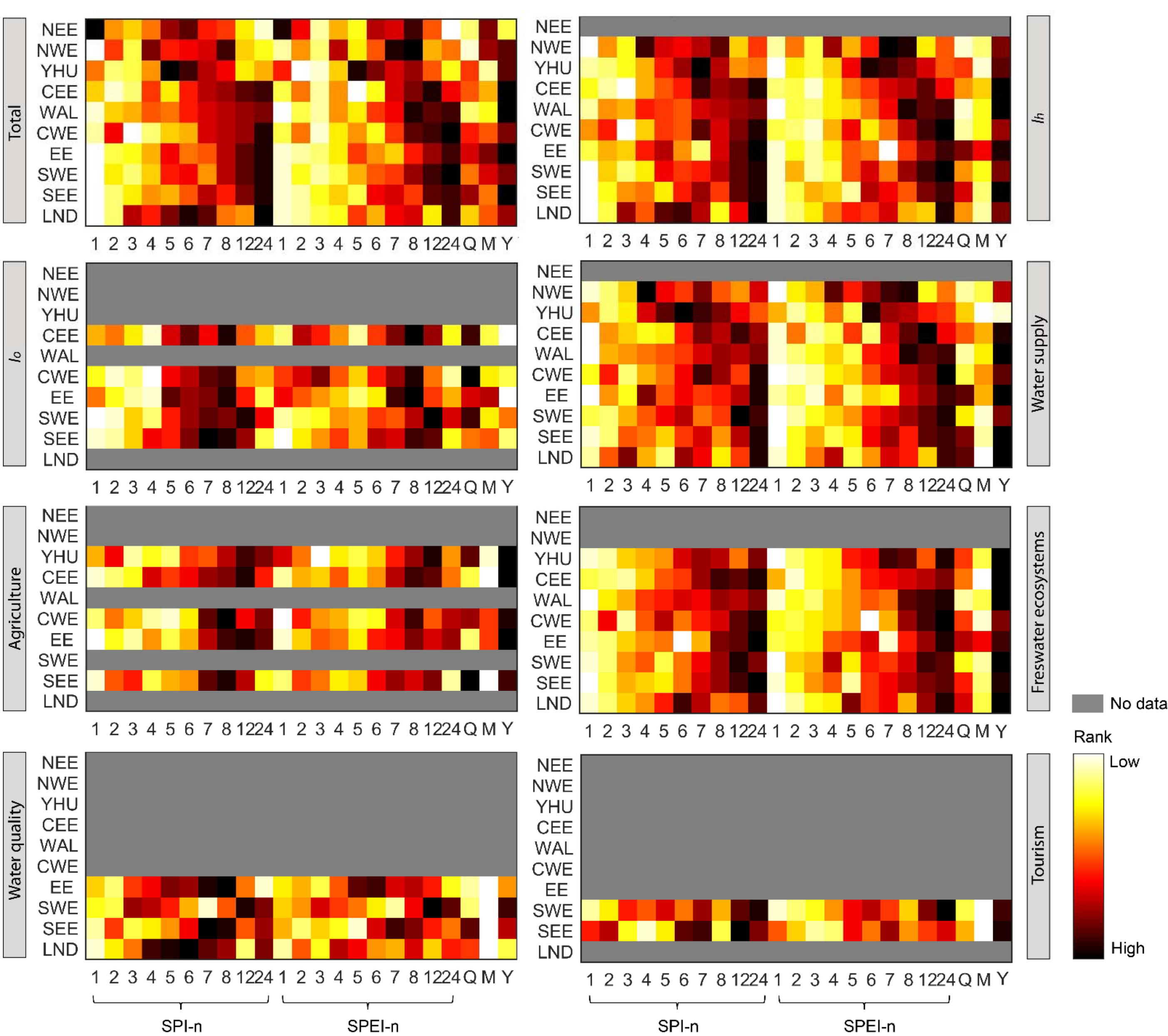


Figure 5: Germany: rank correlation coefficients (ρ) between drought indicators and number of impact occurrences for total impacts, hydrological drought impacts (I_h), impacts due to other types of drought (I_o), and selected impact categories per NUTS1 region.

1



Total
Ih
Io
Water supply
Agriculture
Freswater ecosystems
Water quality
Tourism
NEE
NWE
YHU
CEE
WAL
CWE
EE
SWE
SEE
LND
1 2 3 4 5 6 7 8 12 24 1 2 3 4 5 6 7 8 12 24 Q M Y
SPI-n
SPEI-n
No data
Rank
Low
High

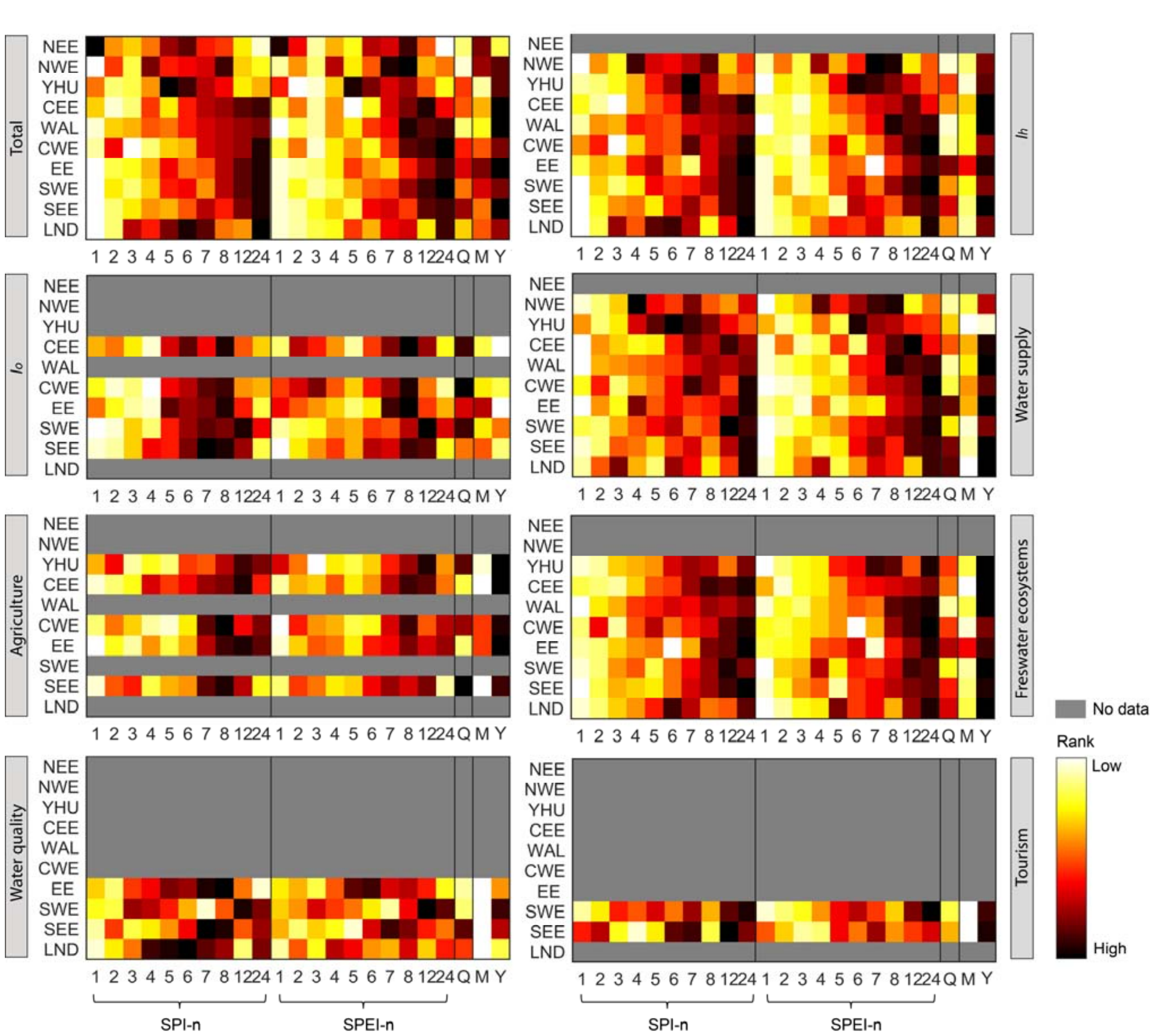
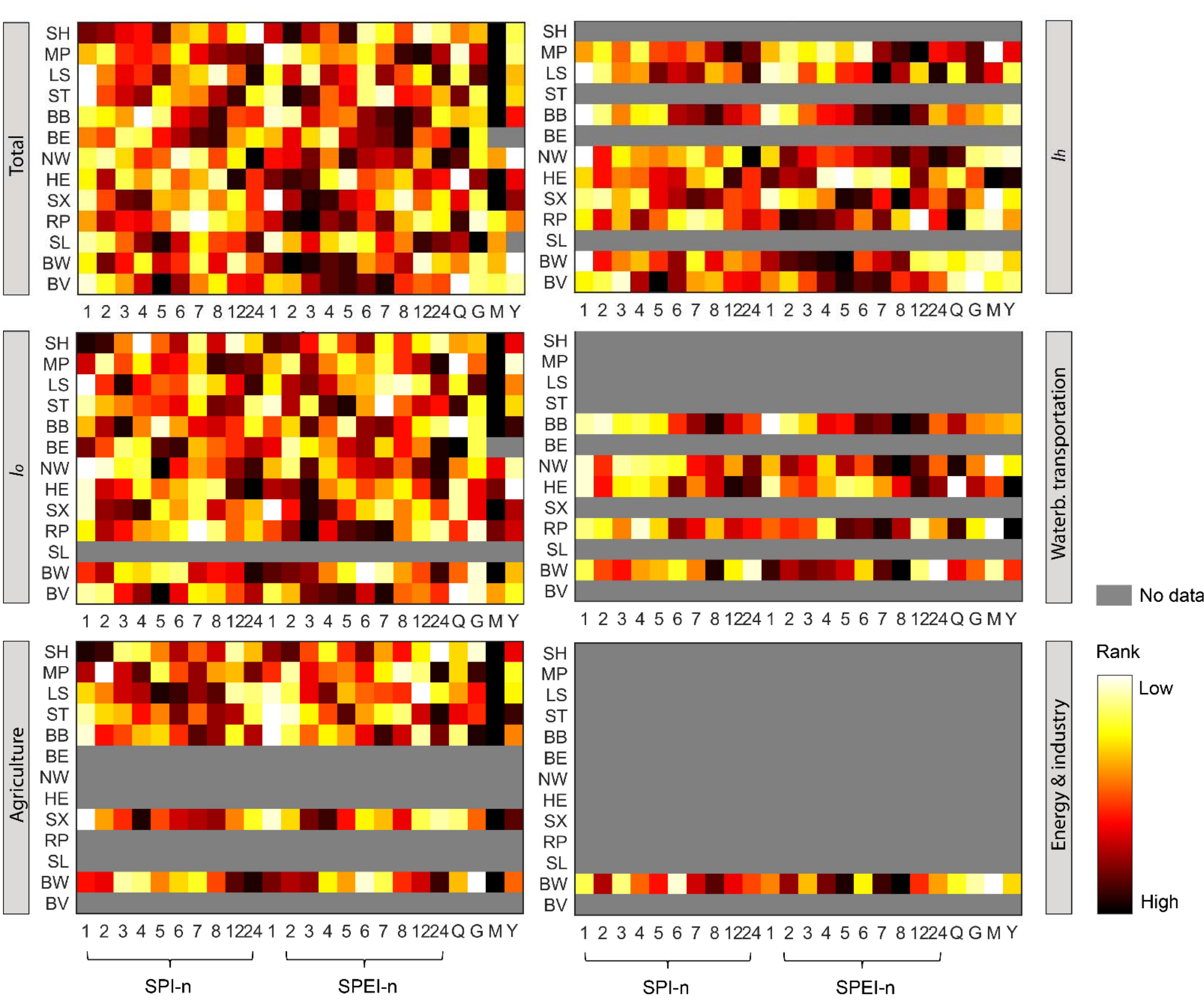


Figure 6: UK: ranks of predictor importance during random forest construction for total impacts, hydrological drought impacts (I_h), impacts due to other types of drought (I_o), and selected impact categories per NUTS1 region.



Total
I_h
I_o
Waterb. transportation
Agriculture
Energy & industry
SH
MP
LS
ST
BB
BE
NW
HE
SX
RP
SL
BW
BV
1 2 3 4 5 6 7 8 12 24 1 2 3 4 5 6 7 8 12 24 Q G M Y
SPI-n
SPEI-n
No data
Rank
Low
High

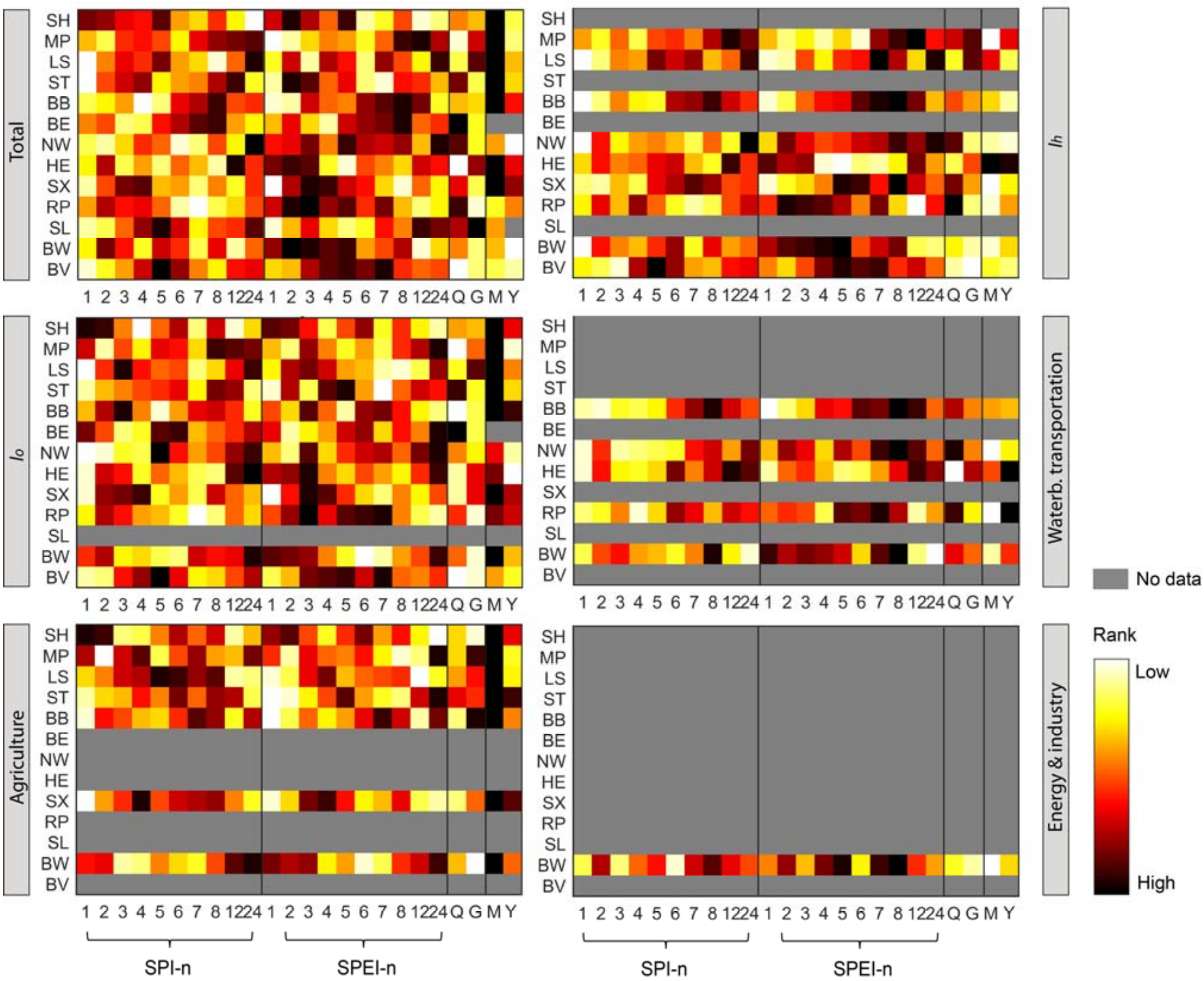


Figure 7: Germany: ranks of predictor importance during random forest construction for total impacts, hydrological drought impacts (I_h), impacts due to other types of drought (I_o), and selected impact categories per NUTS1 region.

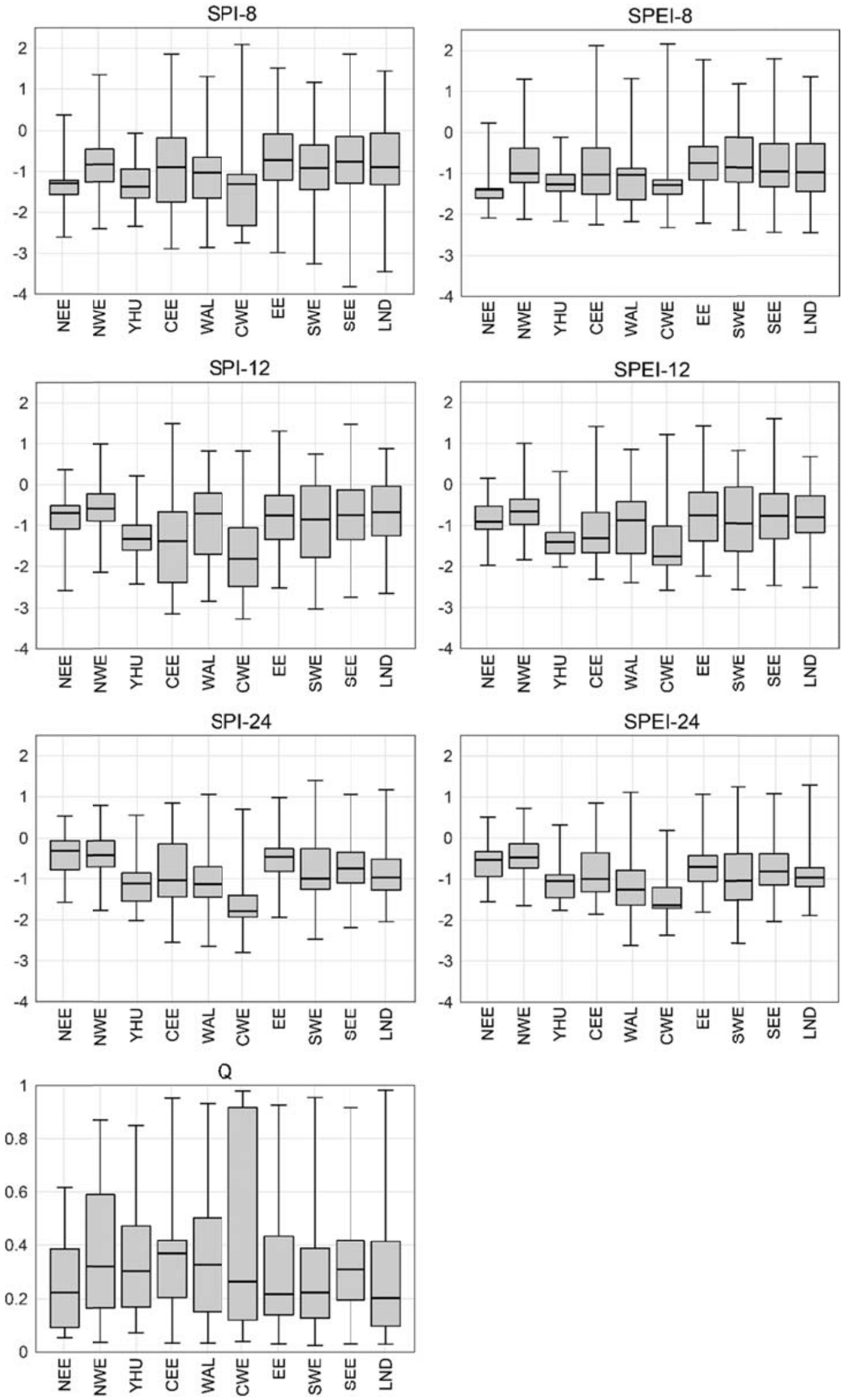


Figure 8: UK: distribution of splitting values during random forest construction (i.e. thresholds of impact occurrence) for selected drought indicator variables for each NUTS1 region. The boxplot whiskers extend to the minimum and the maximum of the distribution, the box encompasses the interquartile range, and the line inside the box displays the median.

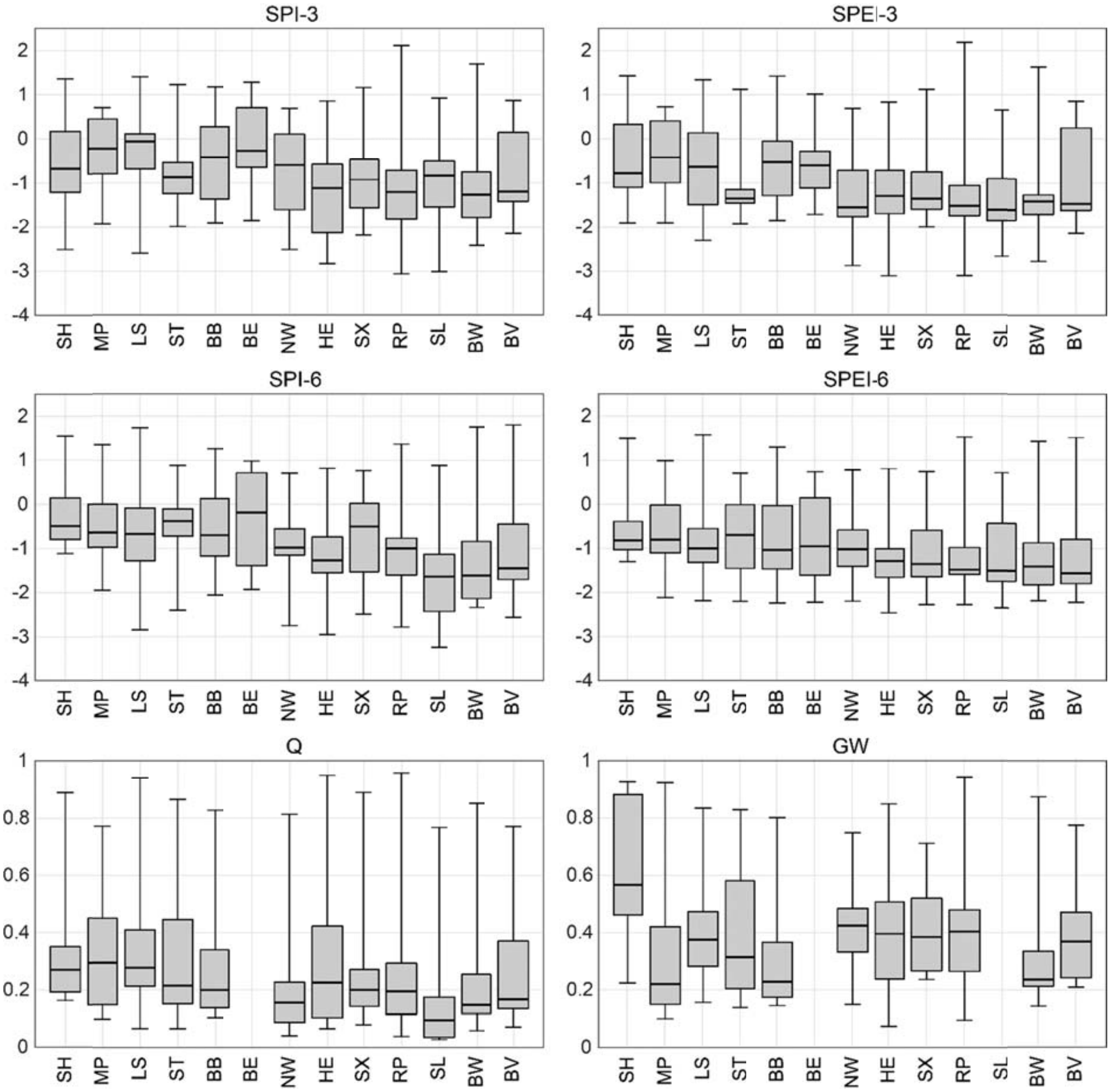


Figure 9: Germany: distribution of splitting values during random forest construction (i.e. thresholds of selected drought indicator variables for each NUTS1 region. Boxplots as Figure 8.

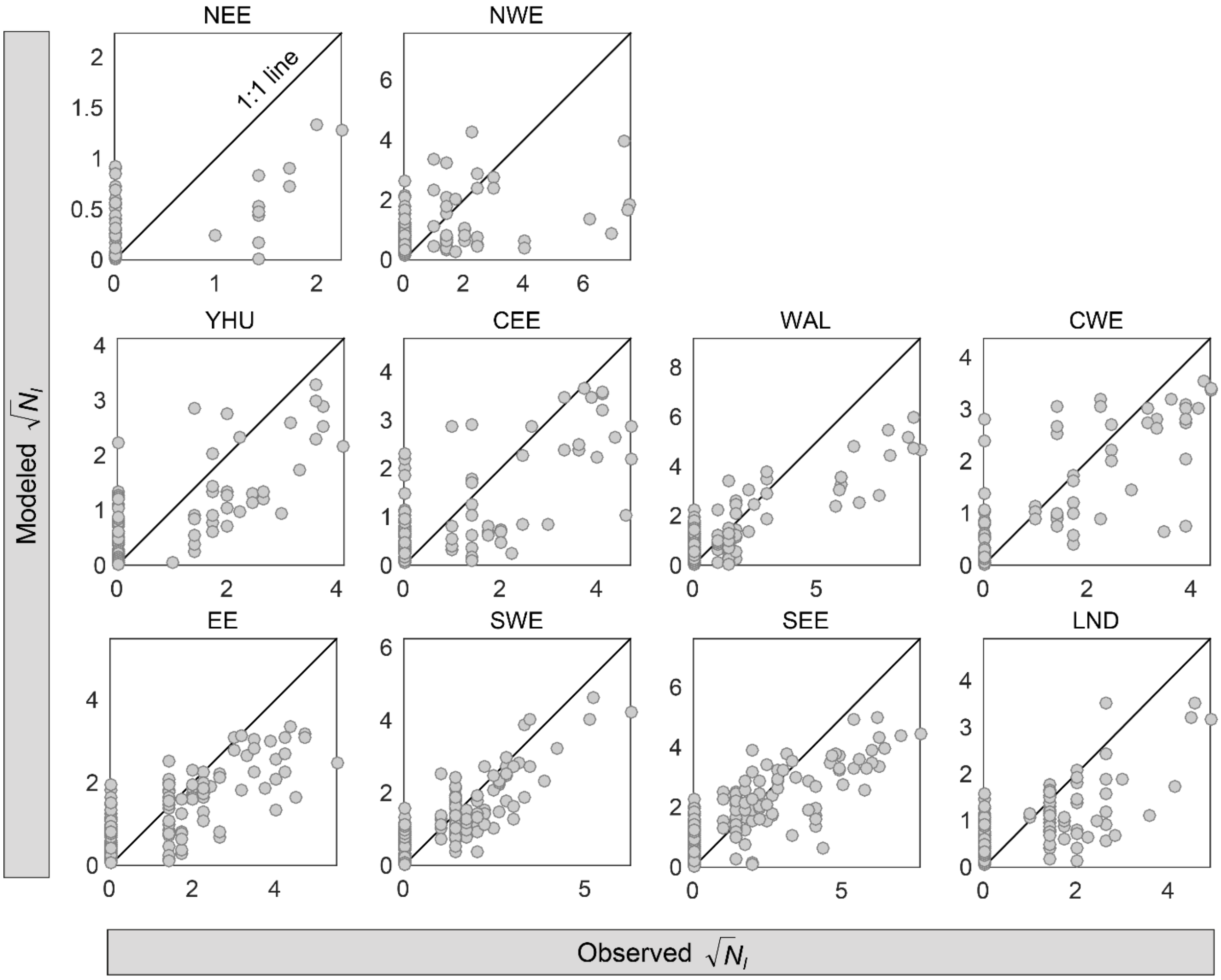


Figure 10: RF Predictions for different regions in the UK (transformed variables).

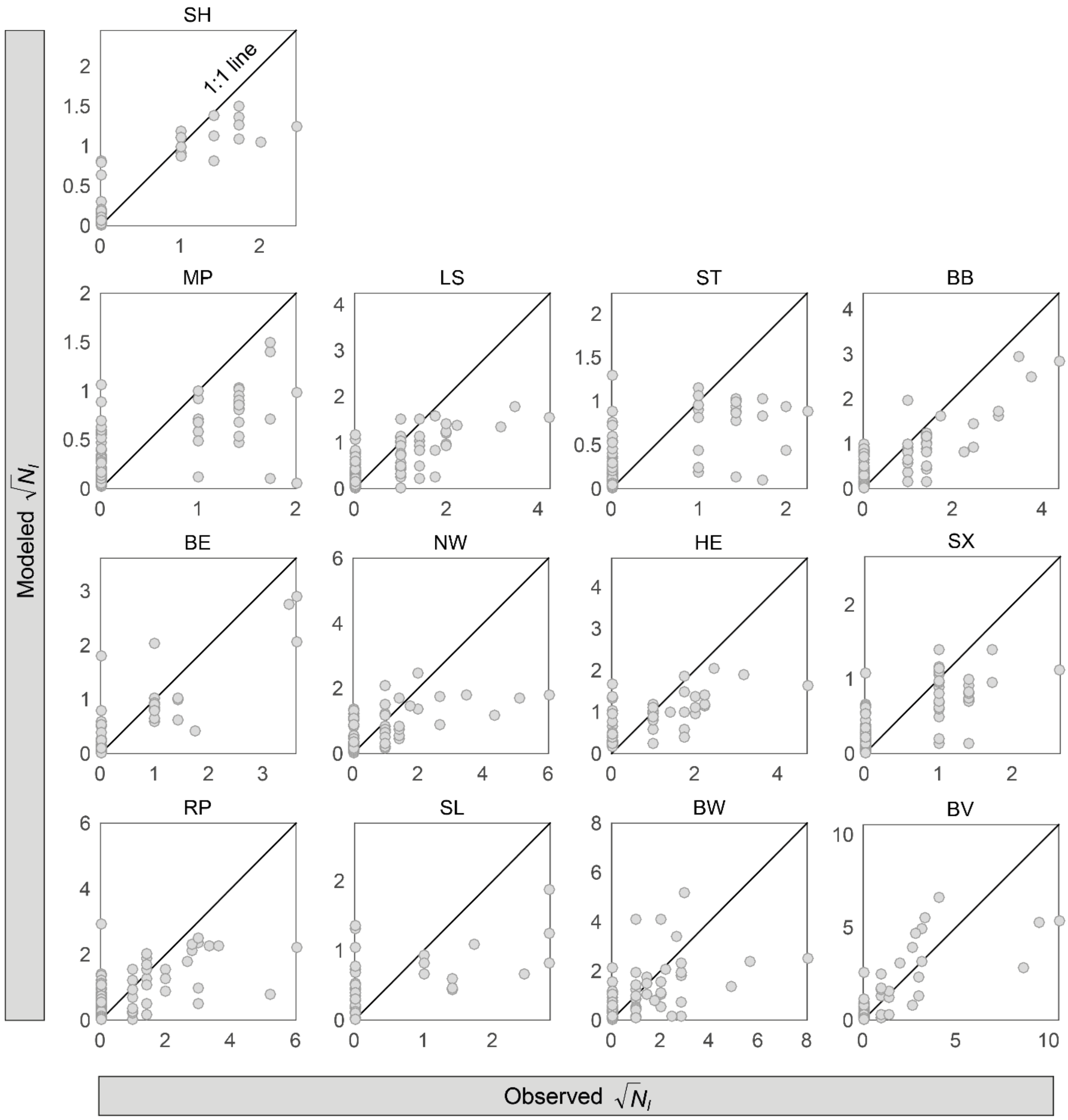


Figure 11: RF Predictions for different regions in Germany (transformed variables).

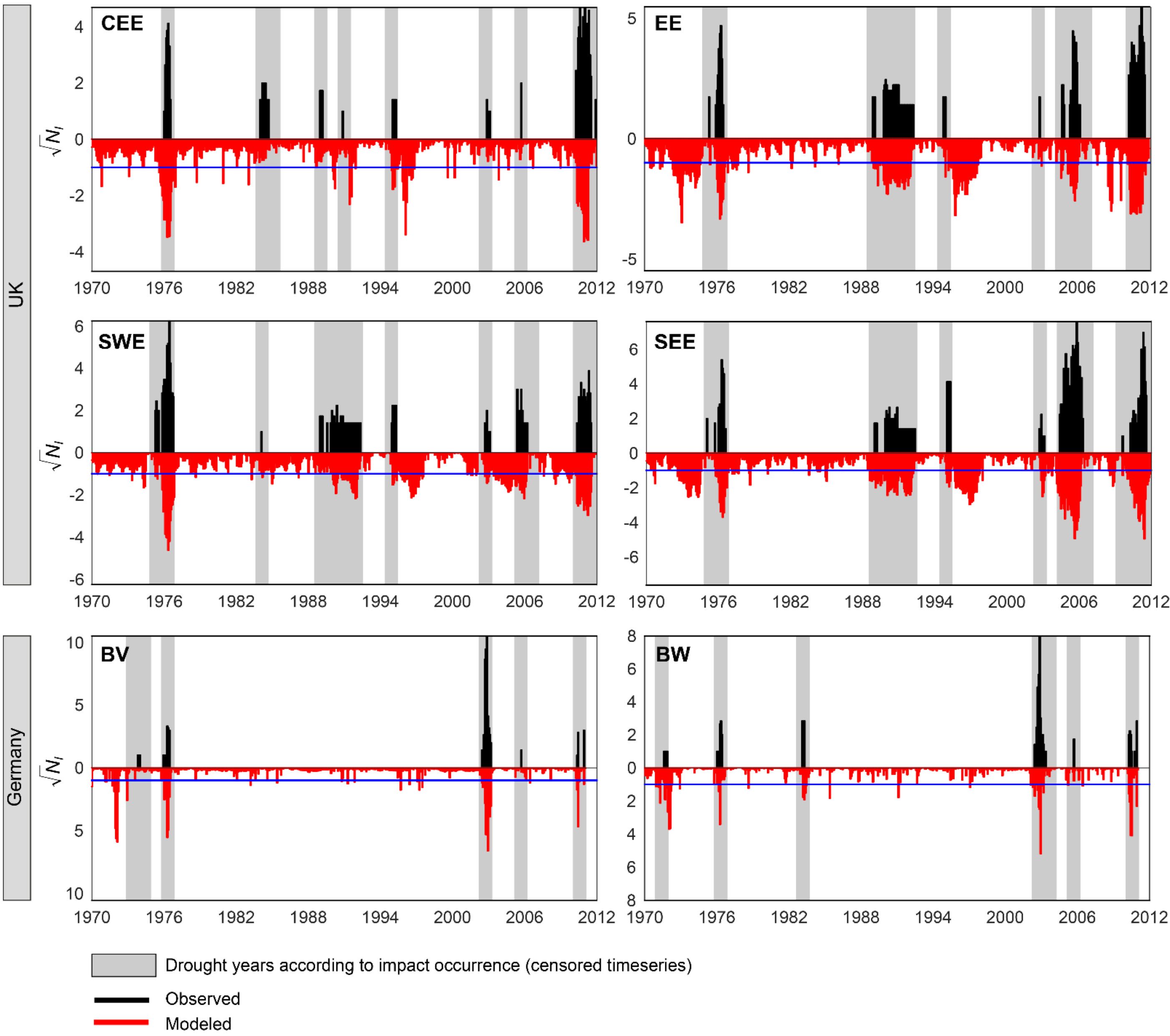


Figure 12: Time series of observed and modeled number of impact occurrences for a selection of NUTS1 regions in the UK and Germany (transformed variables). Grey background: RF Predictions, white background: RF Backwards Learning. The blue line indicates an impact threshold of one: modeled impacts smaller than one should be regarded as absent impact.