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How well do meteorological indicators represent agricultural and forest drought across Europe?

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Abstract

Drought monitoring and early warning (M&EW) systems are an important component of agriculture/silviculture drought risk assessment. Many operational information systems rely mostly on meteorological indicators, and a few incorporate vegetation state information. However, the relationships between meteorological drought indicators and agricultural/silvicultural drought impacts vary across Europe. The details of this variability have not been elucidated sufficiently on a continental scale in Europe to inform drought risk management at administrative scales. The objective of this study is to fill this gap and evaluate how useful the variety of meteorological indicators are to assess agricultural/silvicultural drought across Europe. The first part of the analysis systematically linked meteorological drought indicators to remote sensing based vegetation indices (VIs) for Europe at NUTs3 administrative regions scale using correlation analysis for crops and forests. In a second step, a stepwise multiple linear regression model was deployed to identify variables explaining the spatial differences observed. Finally, corn crop yield in Germany was chosen as a case study to verify VIs' representativeness of agricultural drought impacts. Results show that short accumulation periods of SPI and SPEI are best linked to crop vegetation stress in most cases, which further validates the use of SPI3 in existing operational drought monitors. However, large regional differences in correlations are also revealed. Climate (temperature and precipitation) explained the largest proportion of variance, suggesting that meteorological indices are less informative of agricultural/silvicultural drought in colder/wetter parts of Europe. These findings provide important context for interpreting meteorological indices on widely used national to continental M&EW systems, leading to a better understanding of where/when such M&EW tools can be indicative of likely agricultural stress and impacts.

Introduction

Drought monitoring and early warning (M&EW) is an important component of agricultural and silvicultural risk management. Operational M&EW systems for drought hazard assessment often cover large, continental scales. Examples include the European Drought Observatory (EDO: edo.jrc.ec.europa.eu/), the US Drought Monitor (USDM: http://droughtmonitor.unl.edu) and other regions globally (www.drought.gov/gdm/). Meteorological indicators such as the Standardized Precipitation Index (SPI) (McKee *et al* 1993) are widely used in these systems. Stakeholder participation has started a process to improve drought information systems to better consider drought impacts and provide possibilities to downscale to local conditions (Collins *et al* 2016, Lackstrom *et al* 2017). Meteorological drought does not necessarily equate to agricultural drought, particularly at broad scales, given differences in drought susceptibility (e.g. plant-specific vulnerability, soil water holding capacity, irrigation, and other agricultural management practices). Better knowledge and approaches are therefore needed for the representation of regional to local impacts on vegetation. Several agricultural drought indicators exist that aim for direct characterization of such impacts (Sivakumar *et al* 2011, Zargar *et al* 2011). Among those, remotely sensed vegetation indicators (VIs) are easily accessible and offer the most direct possibility to assess impacts on crops and forest, at high spatial and temporal resolution.

A recent review on drought indicators used in operational drought M&EW systems revealed that while the SPI and other precipitation-based indicators are widely used, there is generally less uptake of agricultural drought indicators including VIs into M&EW (Bachmair *et al* 2016). One reason may be the need for long time series of drought related variables to determine anomalies (de Leeuw *et al* 2014). VIs generally cover shorter historic time periods than precipitation and hence will also have different (shorter) climate reference periods. Other reasons may be that vegetation stress does not necessarily translate to true losses and wider drought impacts and vegetation stress may also be caused by other influences than drought. According to the EDO fact sheets, the use of VIs in M&EW thus requires a combination with meteorological information to guarantee causality. These challenges may hinder direct implementation of VIs into M&EW. Research on the relation between commonly used meteorological indicators and VIs, including factors influencing this relation, will help to identify regions or landscapes where these meteorological indicators characterize vegetation stress well, and where there are areas where further indicators may need to be considered for comprehensive drought M&EW and agricultural risk assessment.

A number of studies have assessed the mutual relations between meteorological and agricultural drought indicators including remotely sensed VIs. Some studies further tested the link to crop yield. Most of them deal with a case study region and a subset of indicators, e.g. the relation between different VIs, or between meteorological variables and one VI, or between VIs and crop yield (Balaghi *et al* 2008, Choi *et al* 2013, Gouveia *et al* 2009, Gu *et al* 2007, Lu *et al* 2015, e.g. Zhou *et al* 2012). Studies at the scale of continental M&EW systems have mostly focused on North America (Bolton and Friedl 2013, Ji and Peters 2003, Quiring and Ganesh 2010, Quiring and Papakryiakou 2003) and have tended to be specific to particular types of indicators or crops. A few global-scale studies have assessed the link between climate variables and vegetation response (Vicente-Serrano *et al* 2014, 2013, Wu *et al* 2015).

For Europe, few studies have addressed the link between meteorological drought and agricultural drought at the large, pan-European scale. The correlation between various drought indicators (including VIs) and meteorological drought indices such as the three month Standardized Precipitation Index (SPI-3) (Peled *et al* 2010) or the 12 month Standardized Precipitation Evaporation Index (SPEI-12) (Ivits *et al* 2014) were found to have spatially variable patterns across Europe. These studies considered a continental-scale domain, but they focused on broad regional patterns identified using cluster analysis. In the two large-scale drought M&EW systems that exist for Europe that offer several meteorological indicators and VIs (European Drought Observatory: http://edo.jrc.ec.europa.eu/; Drought Management Centre for Southeastern Europe: www.dmcsee.org/en/home/), their indices for the 'watch level' are based on a compromise—an index that is overall best-correlated to agricultural drought (SPI-3 in studies by e.g. Ji and Peters 2003, Rossi and Niemeyer 2012); in addition the EDO combined indicator uses the SPI-1 to cover the extremes and a VI to indicate the 'alert' stage (EDO fact sheets).

Due to the multi-national and climatically diverse setting, Europe includes a range of crops and agriculture and silvicultural practices. An alternative user perspective of M&EW systems could be to seek guidance to 'custom-pick' a regionally best-suited meteorological indicator, but so far there has been less emphasis placed on understanding what these systems mean in terms of agricultural impacts on the ground. A study linking meteorological indicators of various time scales to reported agricultural drought impacts found longer time scales being more suitable in European countries with irrigation agriculture that relies on reservoirs or groundwater (Stagge *et al* 2015). Especially at the local scale, such variations in vulnerability and response times of drought impacts therefore affect the suitability of meteorological drought indicators. To improve the basis for risk management at smaller scales, a pan-European study of local-scale linkages between meteorological and agricultural drought will be beneficial. More systematically than previous studies, we therefore compare meteorological indicators that accumulate precipitation deficit for a range of time scales to two commonly used VIs, namely the Vegetation Condition Index (VCI) and the Vegetation Health Index (VHI) (Kogan 1995), also distinguishing between different vegetation classes. More specifically, we

- test the variation of accumulation period for which SPI and SPEI is best correlated with the remotely sensed VIs (VCI and VHI) across Europe and between crop versus forest,
- investigate which geographical variables explain spatial patterns of correlation between local-scale meteorological indicators and VIs, and
- assess the correlation between the VIs and crop yield for one example country (Germany: one of the few countries having readily accessible yield data at local scale), to test which VI is more closely linked to agricultural impacts.

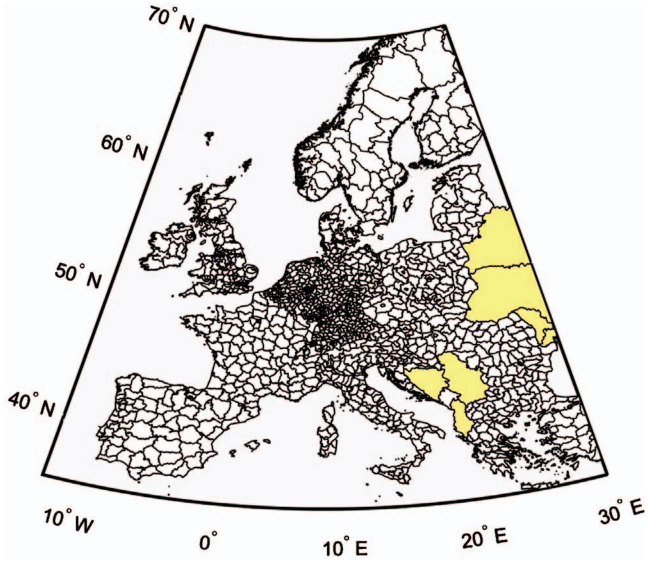

Figure 1. Overview on EU NUTS3 regions (NUTS = Nomenclature of Territorial Units for Statistics). Light yellow regions are not included in EUROSTAT NUTS3 region map version 13.

Our investigation therefore looks in particular at the validity of drought indicators used over large areas with strong spatial contrasts. The analysis also differs from other studies in that it was carried out at the administrative scale of the European Union Nomenclature of Territorial Units for Statistics (NUTS3) regions. Crop yield statistics are commonly aggregated at this spatial scale. It thus represents the scale at which risk management can be carried out.

Data

Meteorological drought indicators and VIs from satellite imagery form the basis of this study. As meteorological indicators we selected SPI and SPEI for the accumulation periods 1–6, 9, and 12 months (hereafter referred to as SPI-n or SPEI-n) with monthly resolution for the period 2000–2015. SPI and SPEI are statistical indicators that compare the total precipitation (SPI) or climatic water balance (SPEI) at a particular location during a period of *n* months with its multiyear average (Sergio M Vicente-Serrano *et al* 2010, Zargar *et al* 2011). SPI is therefore based solely on precipitation anomaly compared to the long-term average for a given length of period, whereas SPEI also takes into account the evaporative demand. SPI and SPEI are based on E-OBS gridded precipitation and temperature data (v12.0, 0.25° spatial resolution) (Haylock *et al* 2008). For detailed explanation of the calculation of the SPI and SPEI see McKee *et al* (1993) and Vicente-Serrano *et al* (2010). Evapotranspiration was determined using the Hargreaves formula (Hargreaves 1994). For SPI and SPEI calculation we used the R package 'SCI' (Gudmundsson *et al* 2014). The monthly time series per grid cell were aggregated at the NUTS3 region level by spatial averaging (see figure 1 for size of NUTS3 regions).

For VIs, time series of VCI and VHI for 2000–2015 were computed based on MODIS NDVI (MOD13C2, 0.05°) and Land Surface Temperature (LST) (MOD11C3, 0.05°) at a monthly time-step to match SPI and SPEI temporal resolution, and then spatially averaged at the NUTs3 region scale. VCI is only based on the Normalized Difference Vegetation Index (NDVI), whereas VHI is calculated as a combination of VCI and Temperature Condition Index (TCI), therefore incorporating the effect of heat induced stress in plants. The equations to calculate VCI, TCI and VHI are described in the supplementary method 1 available at stacks.iop.org/ERL/13/034042/mmedia.

Gridded VIs data and time series are downloadable from CEH Environmental Information Data Centre (http://eidc.ceh.ac.uk/, Tanguy *et al* 2016a, 2016b).

To distinguish between crop and forest cover we used MODIS Land Cover Type data (MCD12C1, 0.05°) for the year 2012. This datasets distinguishes 17 land cover classes. Our class 'crop' subsumes the classes 12 and 14 ('Croplands' and 'Cropland/Natural vegetation mosaic'); our class 'forest' comprises the forest classes 1–5 without any differentiation of forest types (see figure 2 for fraction of crop and forest area per NUTS3 region). While there is inevitably diversity in forest responses, this is a necessary compromise given the pan-European scale of the study.

The following geographical variables per NUTS3 region were used to investigate their effect on the relation between meteorological indicators and VIs: latitude (LAT), longitude (LON), NUTS3 region area (A), elevation (E), annual/winter/summer precipitation totals (P), mean annual/winter/summer temperature (T), soil texture class (SX), percentage of

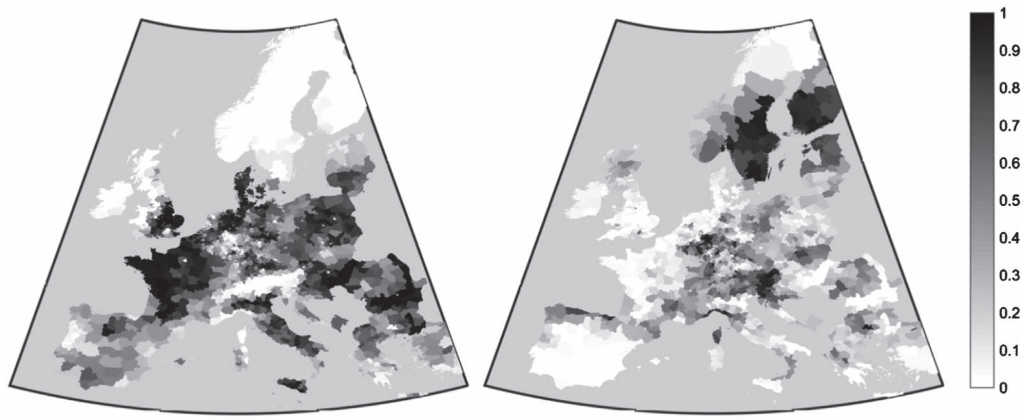

Figure 2. Fraction of crop (left) and forest (right) area per EU NUTS3 region.

Table 1. Overview on geographical variables per NUTS3 region.

Geographical variable	Abbreviation	Spatial aggregation	Source
Latitude	LAT	centroid of NUTS3 region	Eurostat (2013)[a]
Longitude	LON	centroid of NUTS3 region	Eurostat (2013)[a]
NUTS3 region area	A	–	Eurostat (2013)[a]
Elevation	E	mean; range	European Environmental Agency[b]
Annual/winter/summer precipitation	P	sum	E-OBS gridded data v12.0,0.25°
Mean annual/winter/summer temperature	T	mean	E-OBS gridded data v12.0,0.25°
Soil texture class (five classes from coarse to very fine)	SX	majority	European Soil Database[c]
Irrigated area	IA	%	Eurostat LUCAS[d]
Crop area	CA	%	MODIS Land Cover Type Data (MCD12C1, 0.05°) for 2012
Forest area	FA	%	MODIS Land Cover Type Data (MCD12C1, 0.05°) for 2012

[a] http://ec.europa.eu/eurostat/web/gisco/geodata/reference-data/administrative-units-statistical-units/nuts#nuts13.

[b] http://www.eea.europa.eu/data-and-maps/data/digital-elevation-model-of-europe.

[c] http://eusoils.jrc.ec.europa.eu/ESDB_Archive/ESDB/index.htm.

[d] http://ec.europa.eu/eurostat/statistics-explained/index.php/LUCAS_-_Land_use_and_land_cover_survey.

irrigated area (IA), and percentage of crop (CA) or forest area (FA). See table 1 for details.

Crop yields for Germany were available as annual data for several crops for the time period 2000–2015 and these data were assembled from the German regional database (www.regionalstatistik.de/genesis/online). We focused on corn yield in this study given a high fraction of corn cultivation area in Germany and a shorter growing season than for winter grains. Annual crop yield time series were de-trended with a linear trend equation per NUTS3 region (e.g. Quiring and Papakryiakou 2003, Tadesse *et al* 2015), hereafter termed 'crop yield departure'.

Methods

A correlation analysis was carried out between monthly SPI-*n*, SPEI-*n* and the VIs (VCI and VHI) time series from 03/2000 to 12/2015. Only months of the growing season were selected for analysis (hereafter termed 'censored time series'). We assumed a uniform growing season from April until October, which was selected after testing other approaches (see supplementary method 2). Pearson correlation coefficients were calculated between censored time series of SPI-*n* and VCI, SPI-*n* and VHI, SPEI-*n* and VCI, and SPEI-*n* and VHI. Since there is a degree of temporal autocorrelation in the VI and SPI and SPEI time series of longer accumulation periods, which increases the likelihood of Type I error, we corrected the number of degrees of freedom using the modified Chelton method when computing significance levels (Pyper and Peterman 1998). For Germany, we additionally calculated Pearson correlation coefficients between annual time series of corn yield departure and VIs of August; note that we tried different annual VI variables (minimum and mean over the growing season, VIs of different months) but VIs for August provided best results.

To assess which geographical variables (standardized prior to analysis) explain spatial patterns of correlation between SPI or SPEI and VIs we deployed a stepwise multiple linear regression model (independent variables: geographical variables, response variable: correlation coefficient per NUTS3 region).

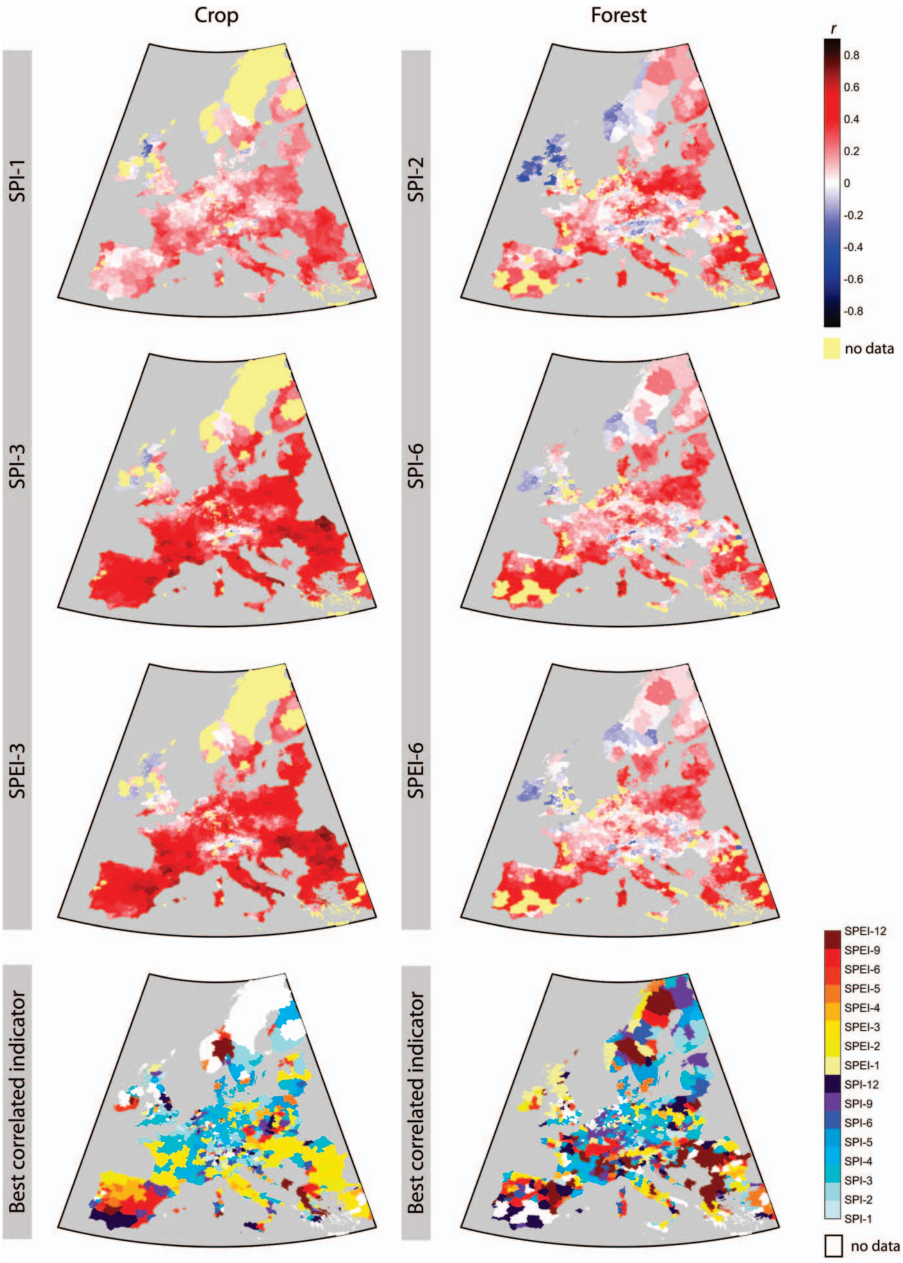

Figure 3. Top six panels: correlation coefficients between VCI and selected SPI and SPEI accumulation periods for crop and forest. The color scale ranges from −0.9 to 0.9. White dots in the centroid of NUTS3 regions indicate p-values < 0.05. Bottom two panels: indicator showing highest correlation with VCI.

For the geographical variables NUTS3 region area (A) and percentage of irrigated area (IA) the data was log-transformed (log(y + 1)). Only NUTS3 regions with complete data for all geographical variables were retained for analysis and NUTS3 regions of overseas territories were excluded ($n = 1148$ after these exclusions). Since annual/winter/summer T, E (mean/range), and LAT are correlated (Variance Inflation Factor > 5), we only kept mean annual T out of these variables. Additionally, partial correlation coefficients and the relative importance of the explanatory variables were calculated for all variables selected in the stepwise model; relative importance is based on the R package 'relaimpo' (Grömping 2006).

Results

The results of the correlation analysis between meteorological indicators and VIs reveal both spatial differences in strength of correlation between SPI-n or SPEI-n and VIs, and differences among accumulation periods of SPI-n or SPEI-n. Also, there are differences in correlation of VCI versus VHI. The maximum strength of correlation for all drought indicator combinations, NUTS3 regions, and vegetation classes is 0.81

For crops, SPI and SPEI accumulation periods of three and four months show highest correlation with VCI (figure 3 left panels). For an accumulation period

Table 2. Results of the stepwise linear regression model, partial correlation coefficients, and relative importance of the selected geographical variables; for abbreviations see Table 1.

Response variable	R^2	Adjusted R^2	Independent variables	Estimate	SE	tStat	pValue	Partial corr. coeff.	pValue	Relative importance metric	Rank of importance
r for VCI vs. SPI-3 (crop)	0.4	0.39	(Intercept)	0.35	0.00	84.7	0.00E+00				
			T	0.07	0.00	15.15	2.12E-47	0.37	6.76E-38	0.13	1
			P	−0.04	0.01	−7.08	2.5E-12	−0.21	1.59E-12	0.12	2
			LON	0.07	0.01	12.85	2.07E-35	0.36	7.14E-36	0.09	3
			A	0.03	0.01	6.65	4.39E-11	0.19	3.48E-11	0.03	4
			CA	0.01	0.00	2.58	1.00E-02	0.08	7.79E-03	0.03	5
			IA	n.s.	n.s.	n.s.	n.s.	−0.05	7.89E-02	n.s.	n.s.
			SX	n.s.	n.s.	n.s.	n.s.	−0.05	8.14E-02	n.s.	n.s.
r for VCI vs. SPEI-3 (crop)	0.46	0.46	(Intercept)	0.34	0.0081.84E+00		0.00				
			T	0.10	0.00	18.52	1.77E-73	0.45	1.88E-57	0.17	1
			P	0.10	0.01	18.07	2.06E-64	0.47	5.06E-65	0.15	2
			LON	−0.03	0.00	−5.44	6.49E-08	−0.13	7.56E-06	0.10	3
			A	0.05	0.01	8.76	6.75E-18	0.26	1.61E-18	0.04	4
			CA	n.s.	n.s.	n.s.	n.s.	0.05	7.36E-02	n.s.	n.s.
			IA	n.s.	n.s.	n.s.	n.s.	−0.06	4.38E-02	n.s.	n.s.
			SX	n.s.	n.s.	n.s.	n.s.	−0.06	4.67E-02	n.s.	n.s.

n = 1148 (number of NUTS3 regions with complete data).

n.s. = independent variables were not selected by stepwise fitr.

of one month the correlation is notably lower and often non-significant. For accumulation periods longer than three or four months the correlation slightly decreases for most NUTS3 regions. Differences between SPI and SPEI are small. For most of central and northern Europe the best correlated meteorological indicator with VCI representing crop area is SPI-3 or SPI-4; whereas it is SPEI-2 and SPEI-3 for most of southern Europe (figure 3 bottom left panel). The strength of correlations varies significantly with southern and eastern Europe tending to have higher values than central and northern Europe. Compared to the rest of Europe, the northwestern UK and parts of Ireland and the Alps stand out through showing very low, zero, or slightly negative correlations.

For forest, similar spatial patterns of correlation are found but the strength is predominantly lower compared to crop (figure 3 right panels). For short accumulation periods of SPI and SPEI, there is a significant negative correlation for Ireland, the northwestern UK, western Scandinavia and for parts of the Alps and Pyrenees. In contrast to crops, there is more diversity in the best correlated meteorological indicators for forest with a clear shift towards longer SPI or SPEI accumulation periods for many NUTS3 regions.

For VHI, the correlations patterns show similarities to those of VCI. However, the patterns are smoother overall, have less pronounced spatial differences, generally higher correlations (especially for accumulation periods of one and two months), hardly any non-significant correlations, and no negative correlations (figure S1 in supplementary material). The best correlated meteorological indicators are SPEI-1 or SPEI-2 for almost the entirety of Europe (both for crop and forest). This is not surprising since temperature is contained in both the VHI and the SPEI.

To investigate whether geographical variables explain spatial patterns of correlation we selected the indicator combination VCI versus SPI-3 or SPEI-3 (table 2). The stepwise multiple linear regression model revealed that 40% of the variance can be explained by the independent variables T, P, LON, A, and CA (table 1). Mean annual temperature and precipitation totals are the two most important variables. Opposite signs of the coefficients indicate a higher correlation with increase in temperature and a decrease in precipitation across Europe. At higher latitudes, *r* decreases, which matches well the observations of zero or negative correlation for NUTS3 regions located in the western coastal UK and Scandinavia. Spatial patterns of *r* between VCI and SPEI-3 for crop are similar to the general observations with a slightly higher percentage of variance explained (46%). Results for forest follow the same general patterns with slightly lower percentage of variance explained than for crop (not shown).

Finally, the correlation between VIs and corn yield departure for Germany based on 16 years of annual data revealed a maximum strength of correlation of 0.93 (see figure S2 in supplementary material). Overall, clear spatial differences are discernible, with higher correlations in the northeast, central, and southeastern parts of Germany (figure 4). The correlation of corn yield departure with VCI is slightly higher than with VHI for most regions. Note that for other crops (not shown) this pattern of slightly higher correlation with VCI is not always found, and also depends on which annual variable of the VIs is used.

Discussion

The correlation analysis revealed that in many parts of Europe, especially in southern and eastern Europe, there is a high correlation between meteorological

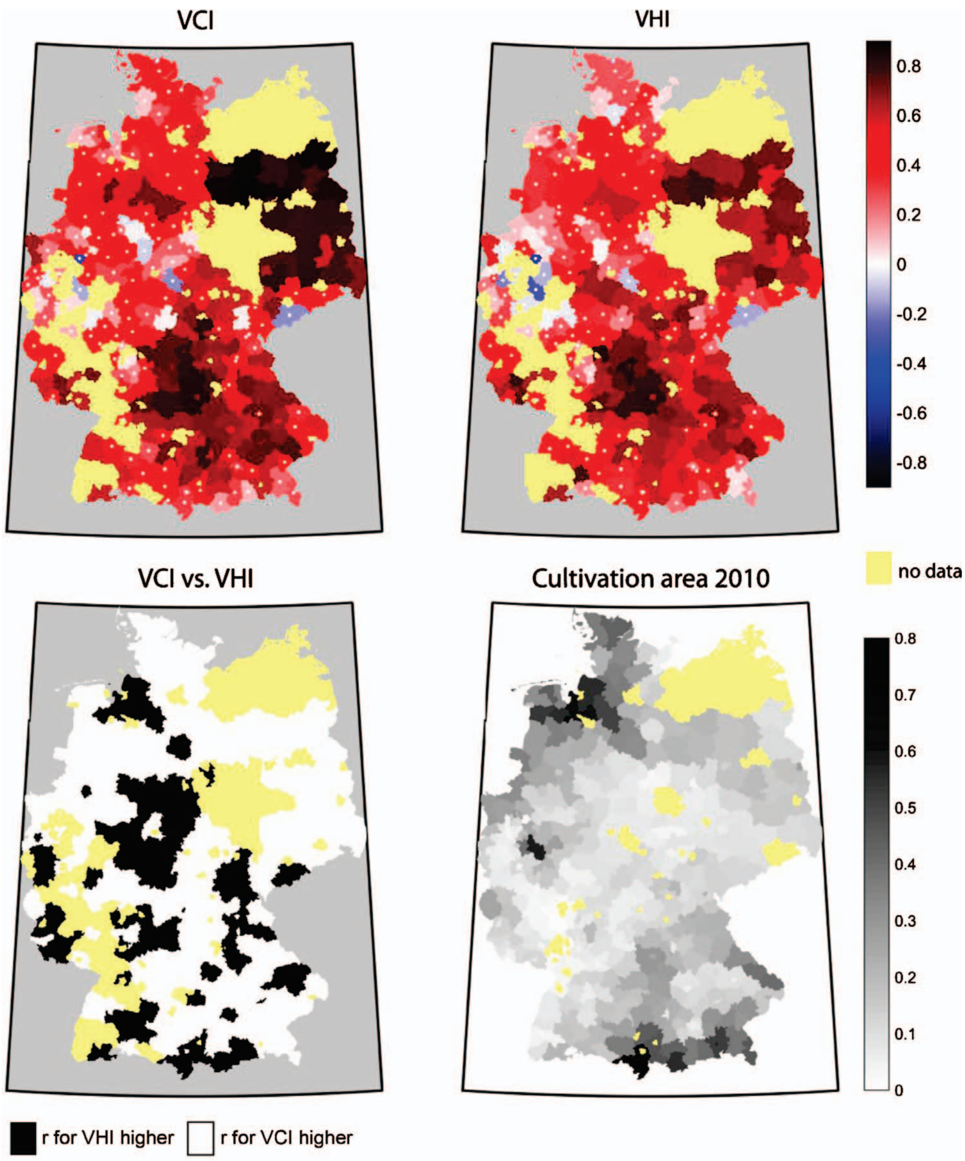

Figure 4. Correlation between VCI or VHI and corn yield departure (top two panels). Bottom panels: indicator with higher correlation; fraction of corn cultivation area in year 2010.

indicators and remotely sensed VIs. There, especially SPEI-3 and SPEI-4 are well linked to vegetation conditions, confirming previous studies and current practice in existing drought information systems displaying these indices. Drought M&EW systems in these regions may therefore be able to reasonably capture vegetation stress using an indicator based on a precipitation or water balance deficit only. However, we reveal that the wettest and colder parts of Europe (northwestern parts of the UK and Scandinavia, and the Alps) display no or negative correlations between VCI and short accumulation periods of SPI and SPEI, especially for forest. These findings suggest that relying solely on meteorological indicators for agricultural or silvicultural risk assessment in these regions might be inadequate, and short precipitation deficit could actually be beneficial for vegetation growth through increased radiation.

Regarding the best correlated meteorological indicator with VCI in central and northern Europe (SPI-3 or SPI-4) versus Southern Europe (SPEI-2 and SPEI-3), the observed results were to be expected, as southern areas have a high evaporative demand which aggravates the effect of precipitation deficit. SPEI incorporates the effect of the evaporative demand through PET. In colder and radiation limited areas, the effect of PET is marginal, therefore SPI which is linked to precipitation deficit, is better correlated to VIs.

Looking more specifically to southern and eastern Spain (especially for crops), we found high correlation of VCI with long accumulation period (SPI or SPEI) (figure 4, bottom left). This observation is counter-intuitive at first, because this is one of the most water limited areas in Europe and we would expect a lack of water to have an immediate effect on crops. It is also surprising that Andalusia (most southern region of Spanish Peninsula), which has extremely high evaporative demand, is better correlated with SPI than SPEI. However, southern Spain's agriculture relies heavily on irrigation, which explains why VIs are better correlated with long accumulation periods, and also why the evaporative demand effect is masked in some cases; crops only start to suffer when there is no water left for irrigation. This also confirms conclusions from Stagge *et al* (2015) who found that longer time scales are more suitable in European countries where agriculture relies on reservoirs and groundwater.

The linear regression between geographical variables and spatial patterns of strength of correlation demonstrated that climate explains a considerable part of the total variance. High temperature and low precipitation increase the strength of that correlation. These results are in line with literature. Several studies have reported a closer link between meteorological drought indicators and VIs or crop yield for climatically drier and warmer areas than for wet, energy limited ones (Karnieli *et al* 2006, López-Lozano *et al* 2015, Peled *et al* 2010, Quiring and Ganesh 2010, Vicente-Serrano 2007). It is somehow surprising that IA was not found to be a significant explanatory variable for the correlations. This might be partially explained by an inaccurate value of IA in official figures. In the case of Spain, some reports suggest that there are between 0.5 (MMA 2000, WWF 2006) and 2 million illegal wells (Fornés *et al* 2005, Llamas *et al* 2001), which would mean that between 20% and 90% of all the water wells in Spain are not registered (Hernández-Mora *et al* 2010).

Our findings on differences between VCI and VHI for some northwestern areas of Europe, and the Alps, also match with the findings of Karnieli *et al* (2010). They investigated the relation between LST and NDVI over a wide range of moisture and climatic regimes in North America and conclude that the commonly assumed negative LST—NDVI relation does not hold true for radiation limited environments. In such regions, indicators based on a negative LST—NDVI correlation assumption, such as the VHI, may be misleading and need to be used with caution (Karnieli *et al* 2010, 2006). The way we calculated VHI for this study is a standard approach. However, a spatially variable contribution of TCI and VCI to VHI rather than a constant contribution, and a positive correlation assumption between LST and vegetation health may be more appropriate for VHI calculation for the wet and energy limited regions of Europe.

Interestingly, similar studies for the US northern Great Plains and Texas found a larger influence of soil textural properties such as total available water content on the correlation between meteorological drought indicators and VIs (Ji and Peters 2003, Quiring and Ganesh 2010). The low explanatory power of soil texture in our study likely results from the relatively coarse soil texture classes we applied (due to data availability). More detailed information on soil properties and management practices could provide additional explanatory power. Nevertheless, the spatial aggregation at the NUTS3 region level, without differentiating between specific crop or forest types, inevitably brings some noise into the relationship between meteorological indicators and vegetation stress.

VHI is generally considered capable of identifying early signs of heat related vegetation stress (Kogan 1997) and therefore may be superior to VCI regarding crop yield predictions. We also assessed how VCI and VHI relate to crop yield in Germany. Our analysis based on corn yield departure did not confirm the superiority of VHI; VCI was for most regions slightly better correlated. On the one hand this may be due to an unknown real contribution of VCI and TCI to VHI. On the other hand, a more detailed analysis would need to be conducted to fully test the performance of VCI versus VHI, e.g. by considering VI values of smaller time windows than monthly data (e.g. Bolton and Friedl 2013, Lobell *et al* 2015, López-Lozano *et al* 2015). Complexities also arise from the absence of a high-resolution crop-specific cultivation map for Germany, and the temporal variation of cultivation area that would need to be accounted for. At the same time, it needs to be pointed out that VIs and crop yield are affected by multiple hazards and management practices and changes are thus not solely attributable to drought. Further information on drought-specific impacts on vegetation, e.g. as present in the European Drought Impact report Inventory (Stahl *et al* 2016), could serve as additional information for assessing the meaningfulness of VCI versus VHI. Nevertheless, the spatial resolution of the data in the EDII and biases in its spatial coverage currently precludes a detailed analysis at the NUTS3 region level.

Conclusion

The details of links between commonly used meteorological drought indicators and remotely sensed vegetation stress at the pan-European scale allow us to make several suggestions to move towards a more impact-oriented drought monitoring and early warning. While a monitoring of SPI and SPEI of two to four months accumulation period as commonly implemented through the SPI-3 will indeed best be linked to crop vegetation stress; for forest, often longer accumulation periods of SPI and SPEI will be required. Secondly, regional differences in our results suggest a generally higher potential for meteorological indices to indicate vegetation drought impacts in southern and eastern Europe than in central and northern Europe. Among the indices SPEI may be a slightly better index in southern and eastern Europe, whereas for the rest of Europe SPI appears to be slightly better. These details suggest that the potential of skilled users to capitalize on drought index information for risk management in their administrative region could be improved by providing background maps where these indices were shown to have been correlated with a certain vegetation stress. Users could then customize their information themselves or use it to build their own regional system.

The northwestern regions in the UK, Scandinavia, and in the Alps with no or a negative relation between VCI and short accumulation periods of SPI or SPEI certainly require different indices to indicate drought impacts. VHI, a combined index based on vegetation condition and temperature, did not show negative correlations with SPI or SPEI for the above regions. We confirm that a negative relation between LST and NDVI for calculating VHI may not be assumed for the wet, energy-limited regions in Europe. Europe's climate and geography hence partly explains the observed spatial patterns of correlation and in climatically drier areas, meteorological indicators may be representative for drought M&EW and hazard analysis. For wetter and colder parts of Europe, however, solely relying on SPI or SPEI for silvicultural or agricultural risk assessment will be inadequate. From a pan-European drought information mapping point of view, our analysis therefore suggests that some regions should better be blanked out or at least marked as showing no link to drought impact on vegetation. In practice, this confirms previous suggestions for more sector-specific M&EW information.

Closing the circle from meteorological to agricultural drought by evaluating remotely sensed VIs with on-the-ground information on vegetation health and agricultural/silvicultural impacts proved a necessary additional step that requires further pursuit. Due to data limitations, we explored the link between VCI or VHI and corn yield departure only for one example country (Germany) and found high correlations (up to 0.9) for certain regions, but also spatial variability. These results suggest that it is worthwhile for administrative regions to collect and provide such information for research that can help customize the use of particular drought information. Overall, such information on the link between multiple layers of drought information may help to further downscale the current monitoring to improve local to regional drought early warning capacity and risk assessment for longer term planning. This would benefit a range of stakeholders such as farmers and growers, agricultural planners and financiers, and environmental managers and regulators. From a research perspective, this can provide a methodological template for similar 'indicator-impact' studies at continental scale. More generally, it advances the science in this area of testing drought indicators to provide 'ground-truth' i.e. verification that these indicators provide meaningful information on likely societal/environmental impacts rather than just meteorological status.

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