Technical Report No. 36

LINKS BETWEEN METEOROLOGICAL DROUGHT INDICES AND YIELDS (1979 – 2009) OF THE MAIN EUROPEAN CROPS

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Date: 10 July 2015

DROUGHT-R&SPI (Fostering European Drought Research and Science-Policy Interfacing) is a Collaborative Project funded by the European Commission under the FP7 Cooperation Work Programme 2011, Theme 6: Environment (including Climate Change, ENV.2011.1.3.2-2: Vulnerability and increased drought risk in Europe (Grant agreement no: 282769). The DROUGHT-R&SPI project started 01/10/2011 and will continue for 3 years.

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Organisations:	Wageningen University, the Netherlands Instituto Superior de Agronomia, Portugal University of Oslo, Norway
Submission date:	10 July 2015
Function:	This report is an output from Work Package 3; task 3.1
Deliverable	This report contributes DROUGHT-R&SPI deliverable D3.5

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Preface

The first author has carried out this study as part of her MSc programme Hydrology and Water Quality, specialization Hydrology and Quantitative Water Management, Wageningen University, Wageningen, The Netherlands.

We would like to thank Drs. Paul Torfs (Wageningen University) for statistical advice and developing some targeted R-scripts to perform the analyses.
Larissa Gunst,

In addition to the DROUGHT-R&SPI project, the research contributes to the programme of the Wageningen Institute for Environment and Climate Research (WIMEK-SENSE) and it supports the work of the UNESCO-IHP VII EURO-FRIEND programme.

Wageningen, 10 July 2015

Abstract

Drought is one of the most devastating hazards worldwide and can impact important sectors humans rely on. One of these is agriculture. Some research has been done to find relations between drought and crop yields mostly on country or regional level. Investigation on these relations for widely cultivated crops on European scale was still missing. To fill this literature gap we used 35-years of observed annual crop yield data of five selected crops (i.e. barley, wheat, sugar beet, potato and maize) and de-trended the data by i) moving average and ii) linear regression to eliminate multiannual trends due to technological development. The crop yield data were related to the meteorological drought indices Standardized Precipitation Index (SPI) and Standardized Precipitation and Evaporation Index (SPEI) given for 1979-2009, both including accumulation periods of 1, 2, 3 and 6 months. For both the drought indices and the crop yield data, information was gathered at NUTS2 level. Statistical models were made on European level and the three biggest climate regions, i.e. Atlantic, Continental and Mediterranean. SPI and SPEI were highly correlated and considered in separated linear statistical models. The models showed that for the SPI as well as for the SPEI the highest correlations were found for barley and wheat in the moving average de-trended data set. SPEI did not give higher correlations than SPI. Impacts of dry spells on crop yield at European scale is visible, but regional differences within biogeographical climate regions exist.

Keywords: drought, observed crop yield, SPI, SPEI, Pan-European

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1 Introduction

Background

Drought is one of the most severe natural disasters in the world, occurring in every climate and can affect even larger areas than floods and earthquakes do (Wilhite and Glantz, 1985; Wilhite 2000a; 2000b; Tallaksen and Van Lanen, 2004). Wilhite and Glantz (1985) assigned droughts into four classifications: meteorological, hydrological, soil moisture (in case of farming referred as agricultural) and socioeconomic. The resulting impacts of droughts can vary for every drought type and region according to the following examples.

In South America, for instance, the Amazon drought in 2005 caused problems in river transportation and crop production (Marengo et al., 2008) and five years later an even more severe drought hit ecosystems and the economic sector in the Amazons again (Lewis et al., 2011; Xu et al., 2011). In ecosystem services Guarín and Taylor (2005) state that tree mortality in Northern California is mainly due to fire in years of drought and in Southern Europe significant correlations between wildfires and drought index SPI (Standardized Precipitation Index) were found (Bifulco et al., 2014; Gudmundsson et al., 2014). Concerning economics, the severe drought of 2002 – 2003 in Australia resulted in income losses up to even 20% (Horridge et al., 2005).

Agriculture is one of the most important drought impacted sectors that humans rely on and directly influence (inter-)national economics and hence can reach a large group of the global population (Tallaksen and Van Lanen, 2004). In the already dry Sahel countries, agriculture is the main source of employment (Boubacar, 2012). During droughts in 2004 and 2010 Traore and Owiyo (2013) found in Northern Burkina Faso that the negative impact of droughts on cultivated crops was higher than on livestock, although the investigated area is situated in a pastoral zone. Within the agricultural sector, droughts are an accruing problem in regions with water scarcity and prone to desertification, like several regions within Mediterranean countries (UNCED, 1992). In addition to already high sensitivity to drought in some parts of Europe, severity will increase in multiple regions of Europe as response to the expected climate change, especially in the southern and central regions (Calanca, 2007; IPCC, 2012). Since Europe is one of the most productive food suppliers and has high yields in Western Europe (Olesen et al., 2010), it is important to explore how anomalies in observed crop yield can be detected by drought indices and to see when the crops are more sensitive during the growing season.

Some research was already done on the relation between crop yield anomalies and drought by simulating actual evapotranspiration and soil moisture for specific crops and soils using time series of weather data. Wolf and Van Diepen (1995) used certain climate scenarios to predict grain maize yields in Europe. In case of climate change, higher yields were expected in northern Europe where as central and southern Europe in general would have about the same or lower yields, respectively. Ewert et al. (2002) determined wheat yield predictions with three crop simulation models and found the models reproducing wheat yield in relation to drought and different CO_2 concentrations well. However, the timing of drought stress needed further investigation.

In the Mediterranean Bordi and Sutera (2007) found the SPI as a useful monitoring tool and likewise the index showed significant relations with crop yields in Sudan (Elagib, 2013). Blauhut et al. (2015) modelled drought risk on pan-European scale for four different impact sectors. Concerning agriculture, the results made clear that another drought index, SPEI (Standardised Precipitation-Evapotranspiration Index), is a significant predictor for drought risk on European scale, but showed a lot of regional differences across the continent. The highest risk of drought on agriculture was found in the Western Mediterranean region, but no distinction was made between different types of crops and here drought timing was missing as well.

Although all work mentioned above on crop yield variations due to drought was approached in different ways, improvements are still needed. Including the distinction between different types of crops might be important due to their variation in water requirements and growing season. Moreover seldom de-trended crop yield data was used to remove the noise from other causes than droughts and therefore a comprehensive study of the effect of drought on crop yield on pan-European scale is still missing.

The lack of adequate spatial and temporal scale data sets made it hard to tackle the research question in the past. Currently the crop yield and climatological data sets are expanded to a European and 30-year lasting scale, allowing to explain past yield trends and variability, to contribute for increasing awareness (e.g. implementation of early warning systems) thus helping mitigate future drought impacts.

Objectives

The aim of this study is to investigate the link between yield of major crops and drought indices by using observed yield and climatological data on a pan-European scale. The in two ways de-trended crop yield data of selected major annual crops will be investigated on a continental scale. In addition, this research will include the suggestion of Ewert et al. (2002) to deal with timing of drought stress including the two common meteorological drought indices SPI and SPEI for multiple accumulation periods. The thesis anticipates to give an answer on the following sub questions:

1. Do two de-trending methods for crop yield (moving average and linear regression) give different correlations with drought indices?
2. Does the drought index SPEI, also accounting for evapotranspiration, give better correlations with crop yield anomalies than SPI?
3. Which accumulation period (between 1 and 6 months) of the SPI and SPEI gives the best explanation of crop yield anomalies? Are the accumulation periods differently significant to determine impacts for the selected crops and are there regional differences on the best accumulation period across Europe?
4. What is the maximum variability in crop yields explained by meteorological drought indices?
5. Are crop yield anomalies and drought indices correlations better explained by accounting differences between biogeographical regions within Europe?

Approach

In this study major annual crops are selected from the Eurostat dataset, available for the period 1975-2009, based on i) a wide spread distribution across Europe, ii) different growing seasons and iii) varying water needs. In order to eliminate multiannual trends due to socioeconomic factors the yield data are de-trended by different methods. Thereafter, crop yield data are related to the meteorological drought indices Standardized Precipitation Index (SPI) and Standardized Precipitation and Evaporation Index (SPEI), both including different accumulation periods up to 6 months. Drought indices and the crop yield data provided information at NUTS2 level and are upscaled to European scale.

The analysis is done separately for each crop by first calculating the correlations between meteorological drought indices and crop yield data for every NUTS2 region. These results were aggregated until the highest spatial scale (European continent) and later on divided over three climate regions within Europe. General linear regression models are intended to be used to describe the most important relations between crop yield anomalies and droughts at different regions.

Outline

In this report Chapter 2 (Methods) gives information about the regions involved and where the data was gathered and how. In addition, it gives background information on the crops and drought indices used. The last section is devoted to the description of the statistical analyses. Chapter 3 (Results) starts with the identification of the best moving average period to compute crop yield anomalies, followed by the significant data when de-trending by linear regression. Then linear relationships between crop yield anomalies and drought indices (SPI and SPEI for different aggregation periods) are explained for each crop. In Chapter 4 (Discussion) the results shown in Chapter 3 are discussed in light of the available information for each crop. In addition data limitations are commented. In Chapter 5 the most important conclusions of the research are summarised and recommendations for further developments and investigations are given.

2 Methods

2.1 Study area

This study encompasses the area in Europe for were both crop yields and climate data are available. It includes the EU members in 2013, Norway, Turkey, Liechtenstein and Switzerland, which are organised in ca. 300 NUTS2 (Nomenclature of Territorial Units for Statistics, level 2) regions. The NUTS2 level is in most cases comparable to province level. NUTS2s are unequal in size, with the largest one in Finland of 226.775 km^2 while most NUTS2 do not have an area larger than 50.000 km^2 (Eurostat, 2011). For Estonia, Latvia and Lithuania the NUTS2 scale is on country level and nevertheless these are not bigger than some regions in Spain, Sweden and Finland. Figure A1.1 and Table A1.1 provide some background information about the NUTS2 locations and codes.

During the years some borders between the regions have been changed. Most impacted was Finland (Table A1.2), where three out of five regions changed their border drastically. Since drought indices were still given for the original region, FI1B, FI1C and FI1D had to be excluded from further analysis.

Based on the natural vegetation maps of Europe (Noirfalise, 1987), Roekaerts (2002) conducted a distribution within Europe of several biogeographical (climate) regions, of which eight of them (i.e.: Alpine, Anatolian, Atlantic, Black sea, Boreal, Continental, Mediterranean and Pannonian) are included in our study. Figure 1 indicates that the climate regions vary in total area and number of NUTS2 regions.

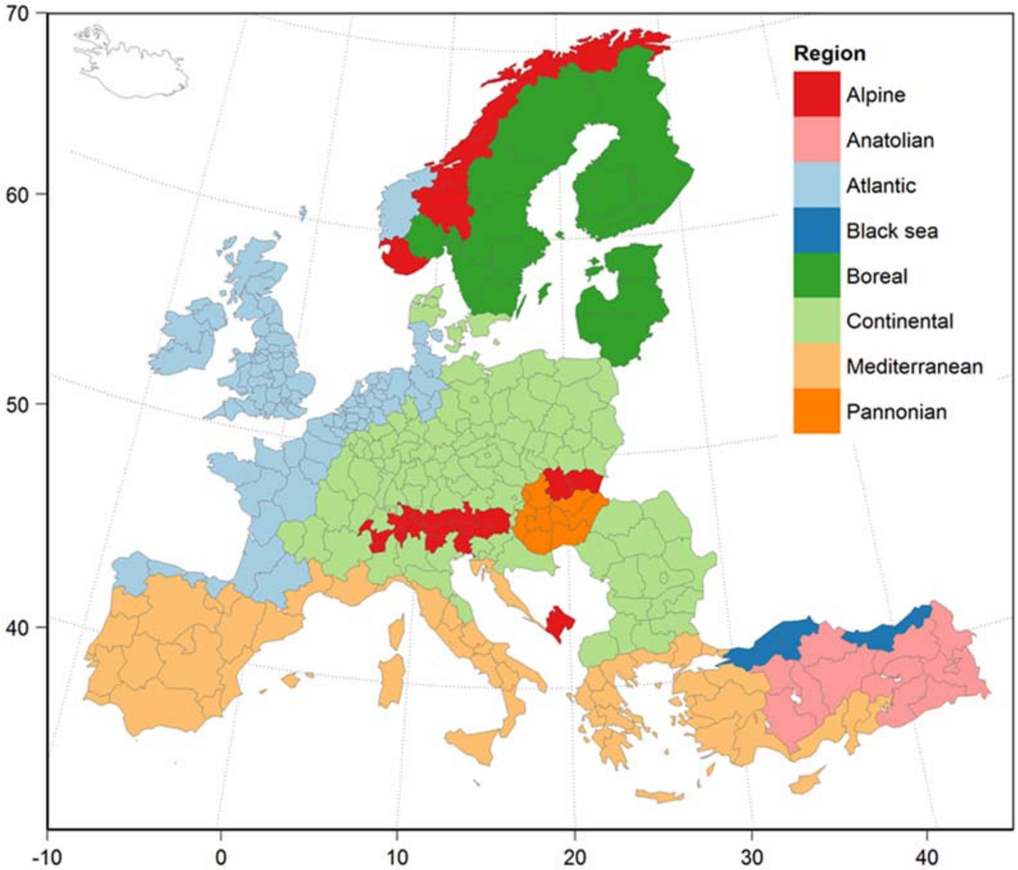

Figure 1: Biogeographical regions (Roekaerts, 2002) of the study area in Europe overlying NUTS2 borders.

These climate regions, although based on natural vegetation, were assumed to have a match with crop performance across Europe. Since RO22 (South-East Romania) was the only NUTS2 with a Steppe Climate it was allocated to the Continental Climate for the purpose of this study. One has to consider though that crops are human planted and therefore the biogeographical regions (where the natural vegetation is dependent on e.g. a combination of orography, temperature and precipitation) could be misleading. To avoid this, seasonal precipitation maps on NUTS2 level were investigated (Figure 2). The maps have a good correspondence with the biogeographical map, but show some spatial variation specially in the Mediterranean area during the winter months. The maps are used to give an explanation if for some climate regions the results are less clear than for others.

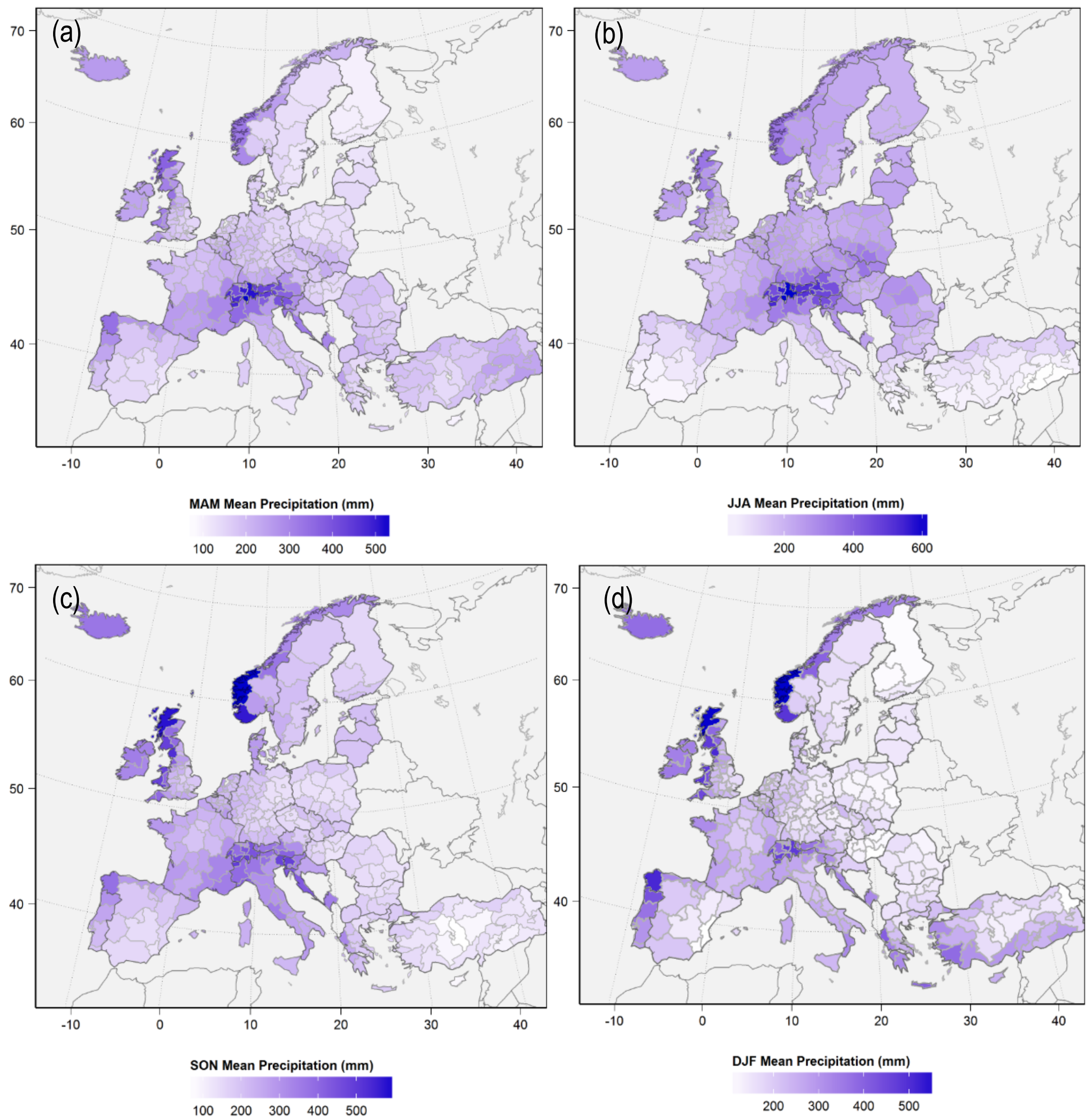

Figure 2: Distribution of average precipitation (1970 – 1999) by NUTS2 in Europe divided over four meteorological seasons: March-April-May (MAM) (a), June-July-August (JJA) (b), September-October-November (SON) (c) and December-January-February (DJF) (d). Data form DROUGHT R&SPI EU project, based on the gridded WATCH Forcing Dataset ERA-Interim (WFDEI) (Weedon et al., 2010; 2011).

2.2 European crop yield data

Eurostat (2014) was used to obtain yearly crop yields on NUTS2 level. Selected crops meet the following criteria:

1. annual crops
2. high availability of data in Eurostat and covering large parts of the European continent
3. both winter and summer crops have to be included
4. differences per crop in (period of) water requirements

Based on the mentioned criteria five crops were selected, i.e.: barley, wheat, sugar beet, potato and (grain) maize. Maize is the only C4 plant (others are C3 crops), and could be considered as more efficient in water use and less respond to drought stress is expected (Nafziger, 2009).

Figures 3 – 7 indicate a wide spread data availability in most climate regions and equal accessibility for most recent members of the EU. Furthermore the maps show that the average yield per NUTS2 region differs a lot within Europe and that the highest yield in each region varies per crop. Within NUTS2 regions temporal variation occurs for even the same crops; the example of Figure 8 illustrates that three random chosen regions in Austria, Belgium and Italy produced unequal amounts of barley in the 70's and 80's of last century, but give about the same yields since of the year 2000. Both AT11 and BE33 declined in production while ITF1 had a big increase in the 90's. Tables A21 – A210 provide more statistics about the number of years, minimum, maximum and average yield per NUTS2 region for each of the five selected crops. One has to consider that the total yearly yield is given and that the NUTS2 regions have varying areas, meaning the values are not given in yield per hectare. Since we are looking for annual changes in crop production along decades, we assume that NUTS areas did not change in between, hence, NUTS2 size is not influential.

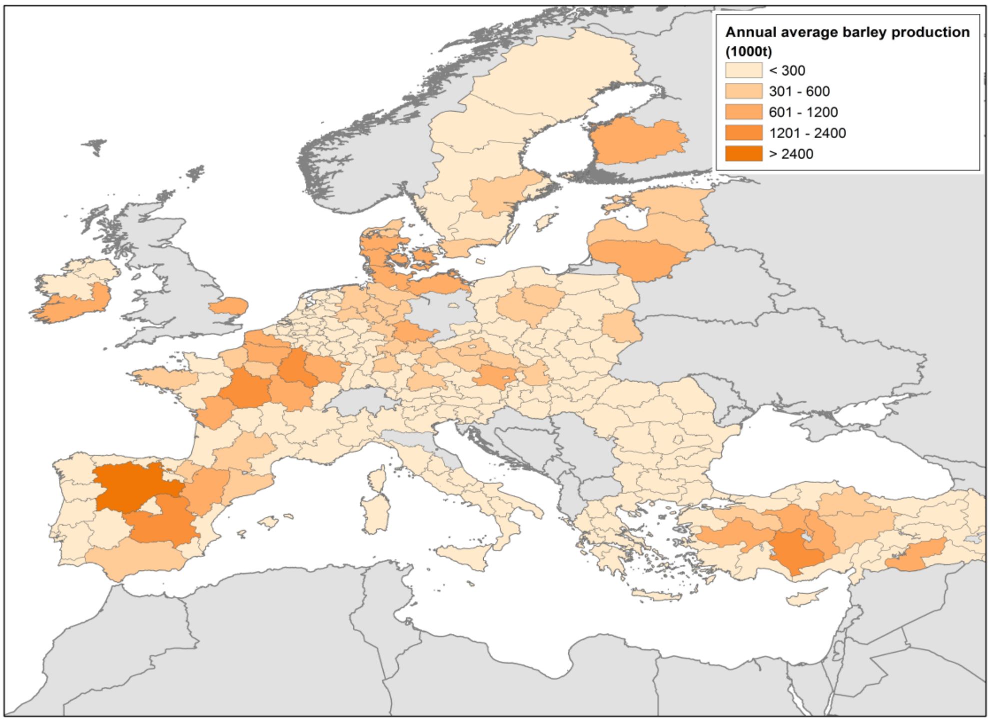

Figure 3: Average yearly barley yield (in 1000 tonnes) per NUTS 2 based on Eurostat data set (1975 – 2009).

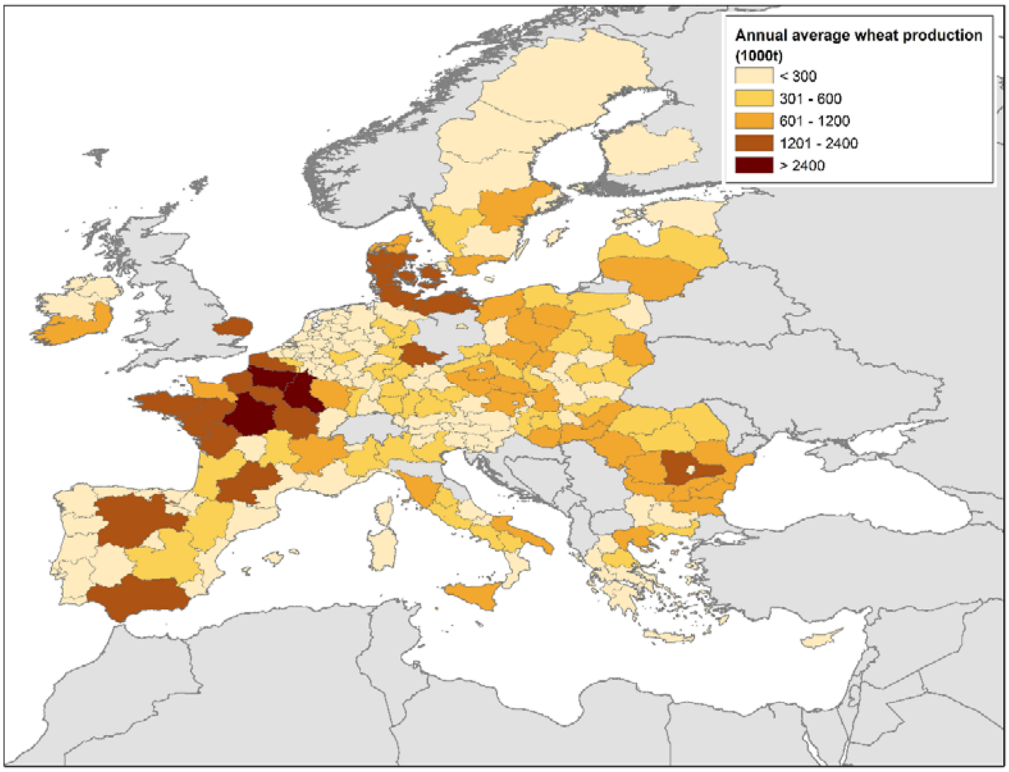

Figure 4: Average yearly wheat yield (in 1000 tonnes) per NUTS 2 based on Eurostat data set (1975 – 2009).

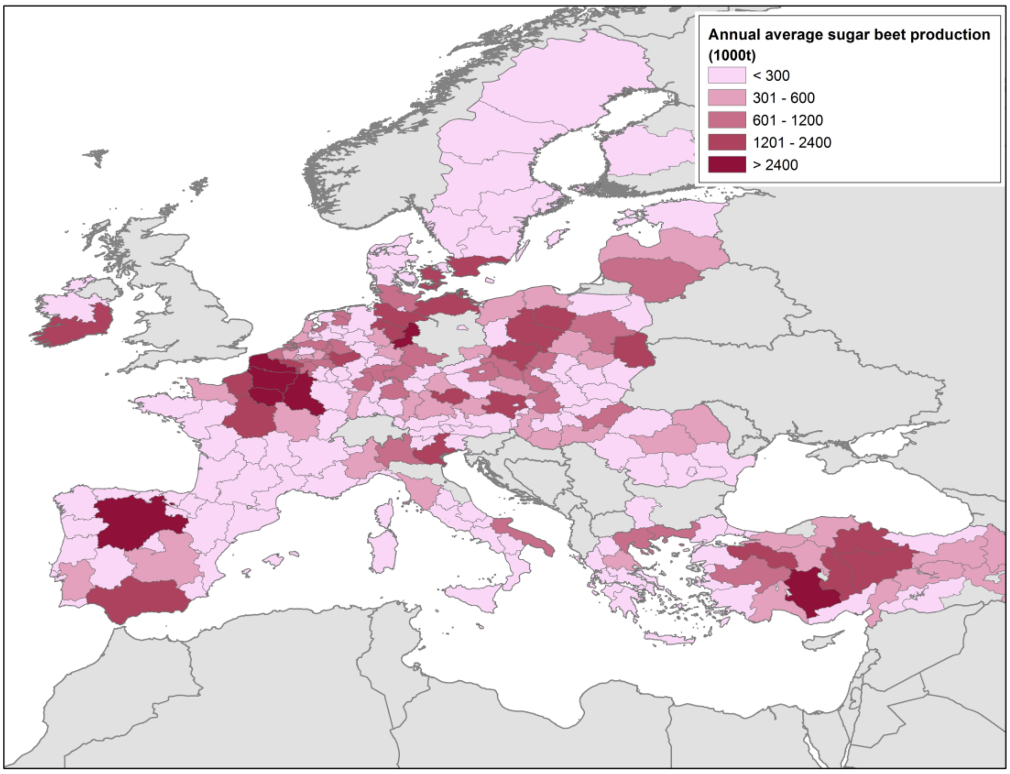

Figure 5: Average yearly sugar beet yield (in 1000 tonnes) per NUTS 2 based on Eurostat data set (1975 – 2009).

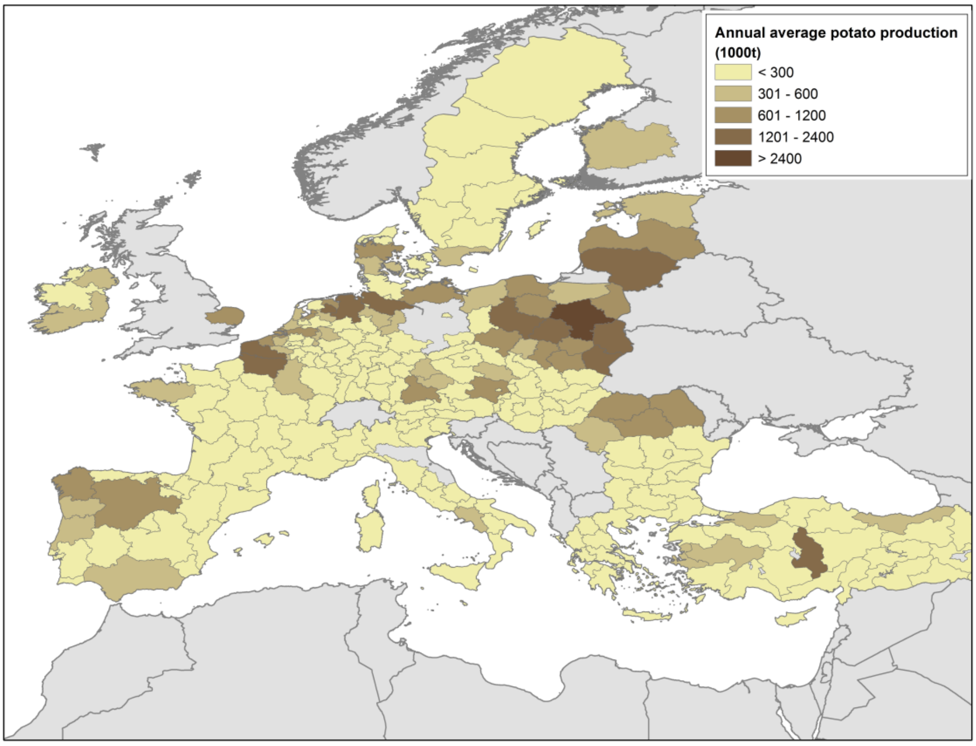

Figure 6: Average yearly potato yield (in 1000 tonnes) per NUTS 2 based on Eurostat data set (1975 – 2009).

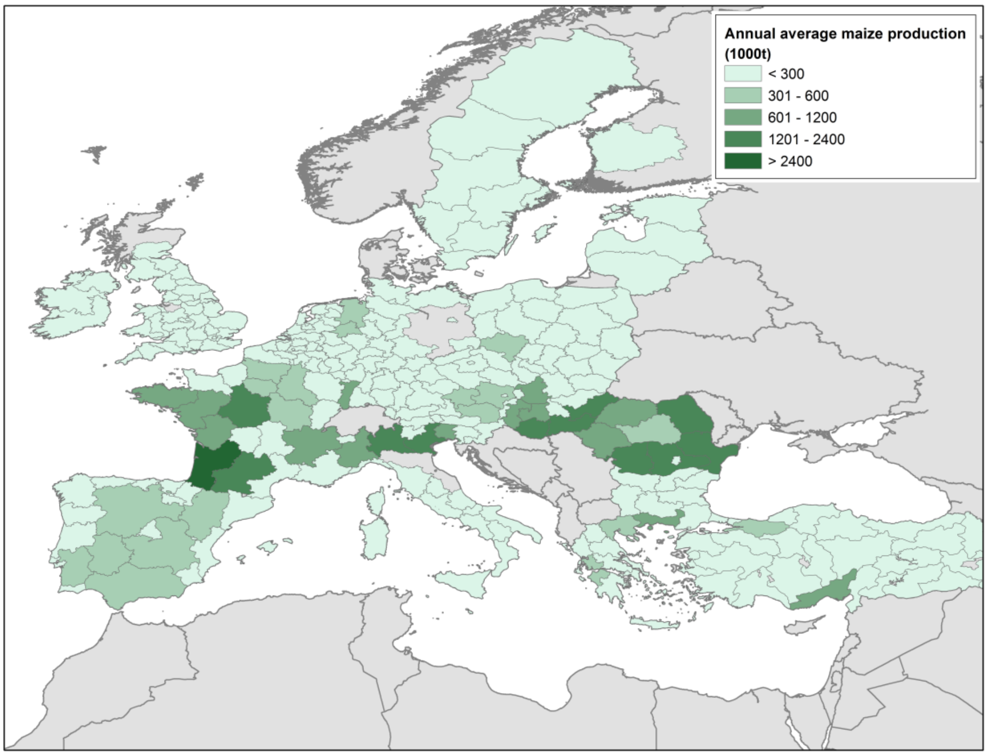

Figure 7: Average yearly maize yield (in 1000 tonnes) per NUTS 2 based on Eurostat data set (1975 – 2009).

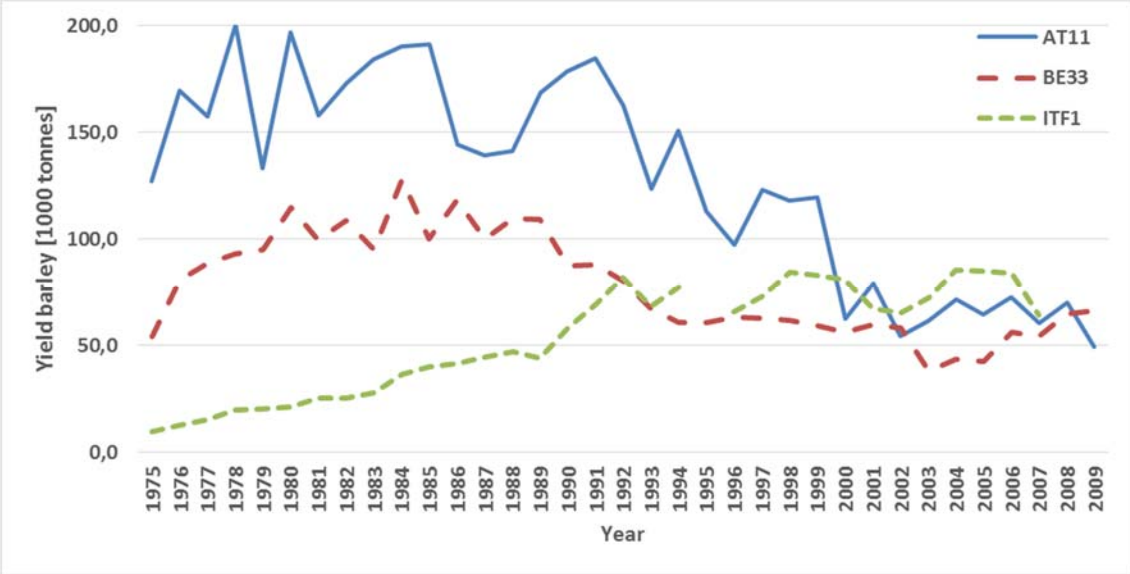

Figure 8: Temporal scale development of the yield of barley for three example regions in Austria, Belgium and Italy: AT11, BE33 and ITF1 (mind the missing data in the years 1995, 2008 and 2009 for this region). While the regions produced unequal amounts in the 70´s and 80´s, the last decennium yields are about the same for all three NUTS2.

For each crop, the start and end of the growing season were identified based on months that were expected to be the first one before seeding until the last possibility of harvesting at European scale. We assume that before and after these so-called candidate months the meteorological conditions do not affect variations in crop yields for these annual crops. This evaluation resulted in three different growing seasons (Figure 9):

- Barley and wheat: September (previous year) – August
- Sugar beet: October (previous year) – September
- Potato and maize: March – October

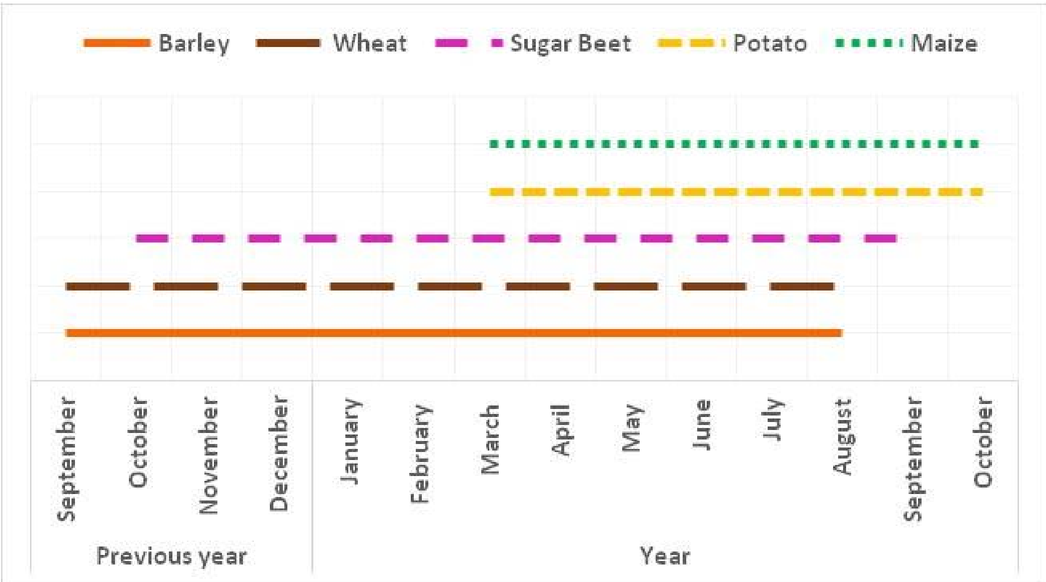

Figure 9: Growing seasons based on candidate months of the five selected crops across Europe (Steduto et al., 2012).

In some Mediterranean areas barley, wheat and sugar beet can be sown in winter, whereas it is considered a summer crop in Northern Europe (Steduto et al., 2012). Nevertheless, since of the lack of a comprehensive overview of which regions follow the winter/spring sowing procedure, we took the maximum growing season for every crop on European scale to compare with drought indices.

Concerning water requirements, the crops are ordered in increasing demands (Table 1). Here the needs are defined as the maximum evapotranspiraton per crop for the entire growing season. The table indicates most water stress, on global scale, could be expected in the end of the growing season, one or two months before harvest (Doorenboos & Kassam, 1979; Steduto et al., 2012; Hlavinka et al., 2009).

Table 1: Water requirements (defined as maximum evapotranspiration per growing season) in increasing order and expected period most sensitive to drought stress for the five selected crops (Doorenboos & Kassam, 1979; Steduto et al., 2012; Hlavinka et al., 2009)

Crop	Water requirements [mm]	Expected period of high sensitivity to water stress
Wheat	450 – 650	April, May, June
Barley	± 500	April, May, June
Potato	500 – 700	May, June, July
Sugar beet	550 – 750	Early start and end of growing season
Maize	500 – 800	May, June, July, August

2.3 Drought indices SPI and SPEI

2.3.1 The calculation method

The drought indices SPI (Standardised Precipitation Index) and SPEI (Standardised Precipitation-Evapotranspiration Index) have been introduced in previous studies and showed high correlations with crop yield anomalies and wild fires in detailed studies worldwide (e.g. Boubacar, 2012; Bifulco et al., 2014; Elagib 2013; Blauhut et al., 2015; Potopová et al., 2015). Both can identify dry and wet spells and include information about the intensity, duration and onset of a drought (or wet period) (Vicente-Serrano et al., 2010). Moreover, SP(E)I are rather easy and fast in calculation compared to other drought indices, of which SPI needs least computations (Vicente-Serrano et al., 2010).

The first index, SPI, is based on the probability occurrence of precipitation cumulated over a selected time scale, mostly months (McKee et al., 1993; WMO, 2012). Since precipitation usually follows a gamma distribution and is skewed to the right (Thom, 1966) a transformation has to be done first by computing the cumulative probability and apply into a normal (Gaussian) distribution (Guttman, 1999), where $\mu = 0$ and $\sigma = 1$. Periods drier (wetter) than average are characterised by a negative (positive) SPI-value and extreme events are indicated by a value equal to/exceeding (-)2.00, see Table 2.

Table 2: Moisture categories for SPI (based on McKee et al., 1993)[1]

Moisture category	SP(E)I
Extremely wet	≥ 2.00
Severely wet	1.50 – 1.99
Moderately wet	1.49 – 1.00
Normal	0.99 – -0.99
Moderately dry	-1.00 – -1.49
Severely dry	-1.50 – -1.99
Extremely dry	≤ -2.00

The second index, SPEI, is an advanced version of the SPI since in addition to precipitation, evapotranspiration is taken into account (Vicente-Serrano et al., 2010). In this multi-scale index potential evapotranspiration (PET) is abstracted from the precipitation. Evapotranspiration determines vegetation water availability and can for this reason: i) better recognise agricultural droughts than the SPI and ii) identify droughts under global warming (Vicente-Serrano et al., 2010).

2.3.2 SP(E)I data set

The SP(E)I data was calculated in previous research for all cells of the European domain within the EU DROUGHT R&SPI project, based on the gridded Watch Forcing Dataset ERA-Interim (WFDEI) on 0.5° x 0.5° spatial resolution (Stagge et al., 2015). Here, the PET was calculated following:

$$PET = \frac{\Delta \cdot R_n + \gamma \cdot \text{"mass transfer term"}}{\Delta + \gamma} \quad (1)$$

where R_n represents net radiation, γ is the psychrometric constant, Δ is the slope of the saturation-vapor-pressure versus temperature curve at the given air temperature and the “mass transfer term” includes the wind speed and pressure/humidity.

The 30-year data set was available for 1979 – 2009, computed against 1970 – 1999 as climate normal for the precipitation. In the next step the data was converted to NUTS2 level with 1, 2, 3, 6, 9 and 12 monthly accumulation periods, of which only the first four resolutions were used in this study as being relevant within the growing season for annual crops. Figures A31 and A32 provide more information about the distribution and pattern of the data.

Figure 10 gives an example (SPI3_5) of how dry and wet spells can vary from place to place. Here, SPI3_5 refers to the 5th month of the year (May) and an accumulation of 3 months (period March – May). The map shows dry areas for the Mediterranean with spring drought in 2005, but meanwhile positive (wet) places occur in Central and Eastern Europe.

SP(E)I data was available for most European counties, except for some in the (South)East, a few (small) islands and the Asian part of Turkey. As such, CY00, ES70, FI13, FI18, FR91, FR92, FR93, FR94, IS00, PT20, PT30, and almost all of Turkey could not be used.

[1] For SPEI the same categories were assumed.

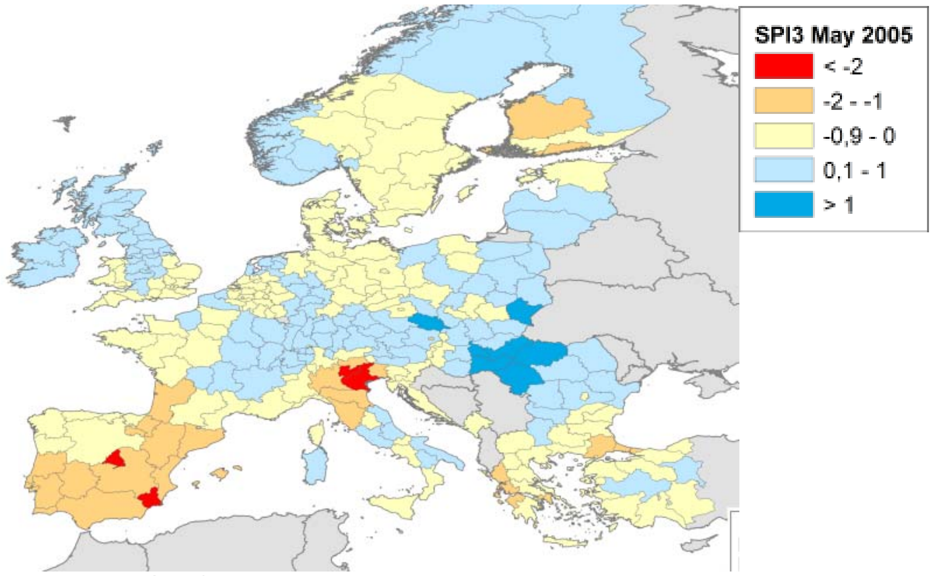

Figure 10: The SPI3 for May 2005 showing a spring drought in Mediterranean, but at the same time wet conditions in Central and Eastern Europe.

2.4 Statistical analysis

2.4.1 Data selection

The selection of crop yield data to be used in this study followed three main criteria:

1) NUTS2 for the two data sets (crop yield and drought indices) were available

2) NUTS2 having at least 10 years of annual crop yield data in a complete sequence. Setting this threshold implied that some new EU members could not be included for analysis. A clear gradient of the available years was found between most West and East European countries, as can be seen in Figure 11 (potato). Longest records were found in the west (>30 years), while in Eastern Europe usually only Greece exceeds 20 years of available data. Germany (DE) was a special case since crop yield data was only available every four years for most regions. No de-trending could be done and therefore most data had to be excluded. The number of years of the other four crops are given in Figures A41 – A44.

3) In order to avoid outliers, NUTS2 regions with an average production smaller than the 10% of the average production in the data set were excluded. Since the crop yield data was available in units of 1000 tonnes per NUTS2, some small regions (or low producing regions) revealed such low values that a reliable de-trending could not be performed and would only scatter the results. Of all NUTS2 regions the average yield over the data set was calculated. The regions with an average lower than the 10 percent of all were then filtered out, making the statistical models more robust. The NUTS2 regions that remained for analysis varied per crop (see Figures 11, A41 – A44).

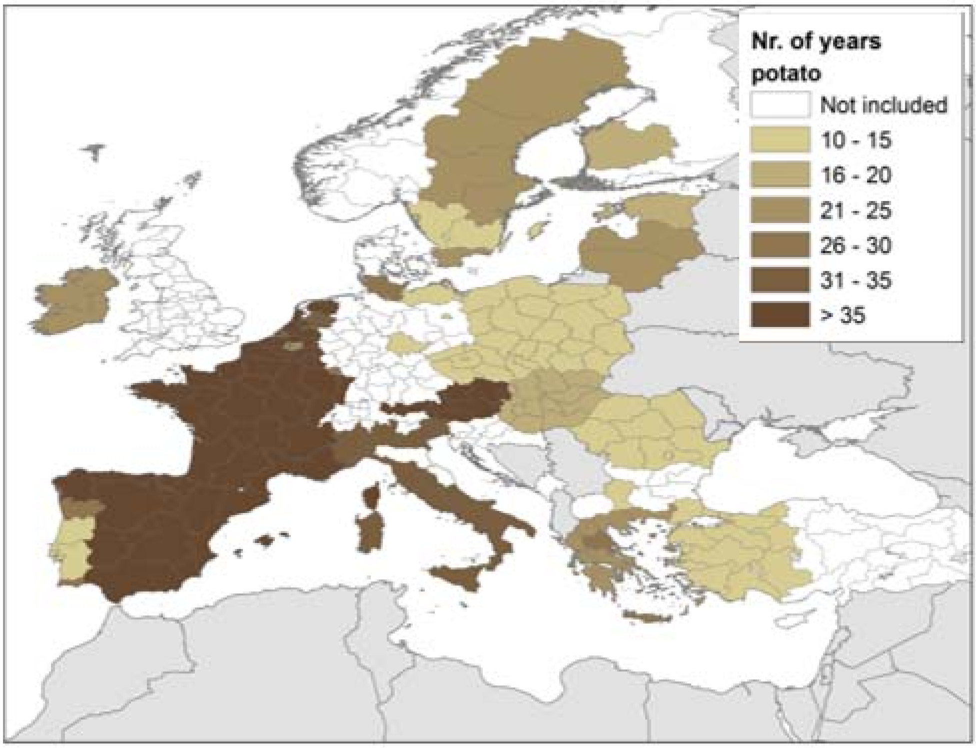

Figure 11: Numbers of years with crop yield data available for potato. Austria, Belgium and the Netherlands contained the longest data set (39 years).

2.4.2 De-trending crop yield data

This study investigates the anomalies in crop yield relative to a reference value for every NUTS2 region separately. In order to obtain these anomalies two procedures were used to de-trend data: (i) moving average, and (ii) linear regression. The procedures differ in approach: while the first one makes multiple trend lines over a chosen period (e.g. every three years), linear regression covers the entire series in once. Since these two approaches are different, both de-trended data sets will not be equal and therefore likely give other results when relating these with the drought indices.

Moving average

For the first method, de-trending by moving average, the best de-trending time period (length) needs to be defined first. A well-established way to do so is by using the partial autocorrelation function (PACF) (Box et al., 1994), in which the number of lags (i.e. years) gives a suggestion of the period that should be used for de-trending. For every NUTS2 region each of the five crops the PACF was calculated with SPSS[2]. Figure 12 illustrates, as an example, for region BE34 that two or three years as time period would be a good decision.

Frequency analysis for the full data set allowed the identification of the most common lags (period of years) that could be applied in the subsequent analysis

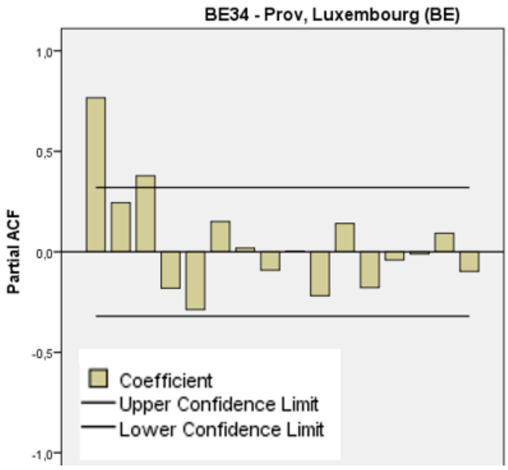

Figure 12: Partial Autocorrelation Function (PACF) of barley in BE34 (Belgium).

2 SPSS: Autocorrelations function in the Forecasting mode.

in which the de-trended yield anomalies were related to the SP(E)I. The following three options were examined:

1. Anomaly (in 1000 tonnes) of the year(s) before (B) the observed annual yield (Ano_B)
2. Anomaly (in 1000 tonnes) of the year(s) before (B) and after (A) the observed annual yield (Ano_B_A)
3. Anomaly of the percentage (in %) of the two calculations before (Ano_B_%), and before and after (Ano_B_A_%).

The first approach is the simplest model and only needs input from the previous year(s). The second one needs data of the following periods; the approach could be a bit more complex but is possibly more accurate. The third method of taking the percentage compared to the moving average series (i.e. standardization by moving average) was done to set all regions to the same scale and will make them easier to compare. The anomaly in crop yield was then obtained by:

$$MA = \frac{\sum_{i=1}^{N} Y_{Raw\ (i)}}{N} \quad (2)$$

$$Ano\ (i) = Y_{Raw\ (i)} - MA \quad (3)$$

$$Ano_{\%}(i) = \frac{Ano\ (i)}{MA} * 100 \quad (4)$$

Where 'MA' is the moving average, 'Y_{Raw}' the raw data set of the year(s) before (and after) without the value of the current year, 'N' is the number of years included, 'Ano' the Anomaly and '$Ano_{\%}$' the Anomaly percentage of moving average. Figure 13 (upper) gives for BE34 barley time series of raw data and the moving average. The anomalies are provided in the lower graph (Figure 13). The anomaly percentage gives a more peaky result than the normal anomaly and could supposedly for this reason detect effects of droughts better.

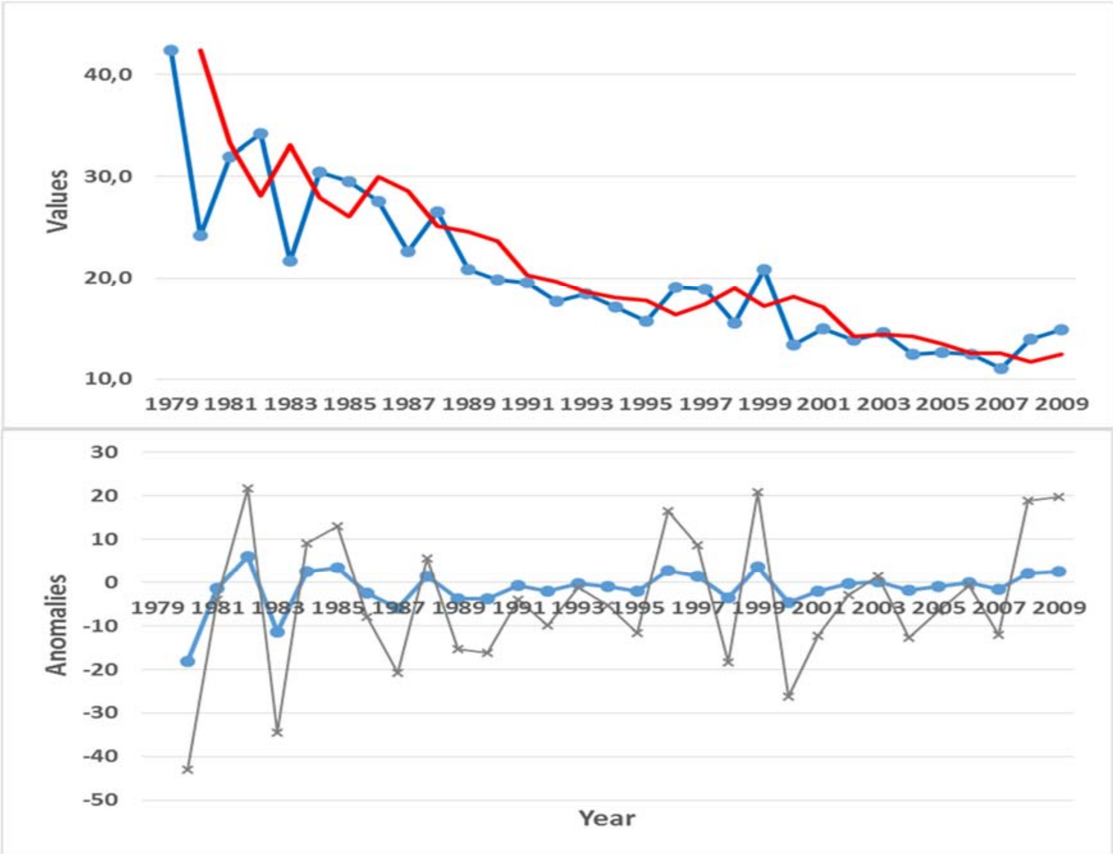

Figure 13: De-trending by moving average, for example, BE34 with barley yield. The upper graph provides the raw data set (blue line with dots) and the trend line (red line) in this case of two years backwards de-trending. The lower graph gives the resulting anomalies (blue line with dots) when the raw data set is subtracted from the trend line. The anomaly percentage (grew thin line with crosses) shows the same pattern, but it is more pronounced.

Linear regression

The second method of de-trending is the linear regression, in which for every NUTS2 region the data series of each crop is de-trended with one linear line. The anomalies were computed with Rstudio[3]. In case linear regression was found with a significance of $p \leq 0.001$ (0.1%) the anomalies were accepted and included for the analysis. In case of using a higher significance level a lot of linear trends were found that did not look linear by eye. Figure 14 proves that both methods provide different de-trending results. For the linear regression the percentage of the raw data set was calculated as well (not included in Figure 14), to make it easier comparing the results of this method and the moving average**.**

[3] Rstudio: comment ‘linmod = lm(values~years)’ (Torfs, personal communication, 2014)

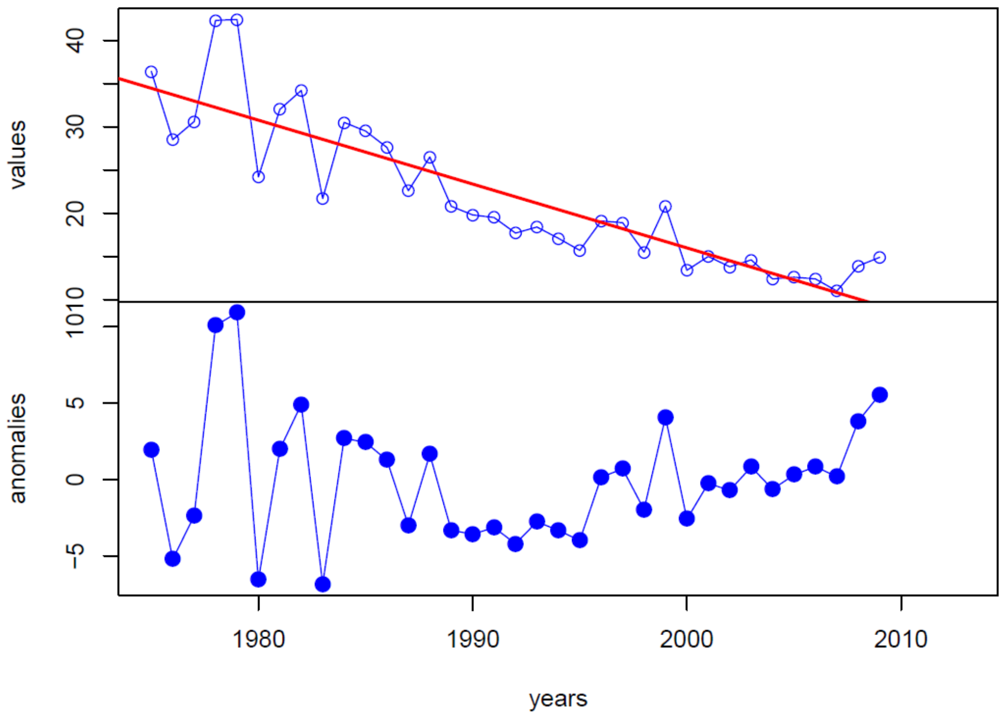

Figure 14: De-trending by linear regression, for example, BE34 with barley yield. The upper graph provides the raw data set (blue line with dots) and the trend line (red line). The lower graph gives the resulting anomalies (blue line with dots) when the raw data set is subtracted from the trend line.

2.4.3 Finding relations between crop yield anomalies and drought indicators using regression analysis

The relations between crop yield and SP(E)I were obtained by linear statistical models using IBM SPSS Statistics software. Preliminary exploration of the data revealed high correlations between SPI and SPEI data for each accumulation period and months (Table 3). Given the high correlation values (Pearson R over 0.960) for the same accumulation periods it was decided to perform separate analysis for assess the effect of each indicator on crop yield changes. Furthermore, SP(E)I6 was highly correlated with the smaller accumulation periods and includes most of the growing season in once, meaning that different impacts with the parts of the growing season could not be detected if SP(E)I6 was included in the models and therefore was excluded from the modelling.

Table 3: Correlations (R) between SPI and SPEI with the same accumulation period

SP(E)I	Pearson R
1_3	0.982
1_4	0.981
2_3	0.977
2_4	0.961
3_3	0.982
3_4	0.969
6_3	0.972
6_4	0.961

Correlation analysis (Pearson R) was also done between the SP(E)Is during the growing season and the crop yield variables (raw data, de-trended using moving averages and de-trended using linear regression). To identify the months and accumulation periods, which are statistically correlated at a significance level of 0.05 with crop yield changes, the analysis was done at NUTS2 level and the results were next lumped at biogeographic climate region and pan-European level.

For each crop, single statistical models were used to identify the relation between annual crop yield anomalies and the precipitation condition calculated as SPI and SPEI.

First, the effect of NUTS2 and climate regions on each crop yield was assessed by ANOVA (analysis of variance) (Statsoft Inc., 2015) to find whether or not NUTS2 and climate regions significantly differ. With the exception of raw data, all other crop yield variables (data from de-trended approaches) did not show significant effect of those two factors (i.e. crop yield of NUTS2 and climate regions).

Thereafter multiple regression modelling was performed to determine the best predictor of crop yield anomalies with the SP(E)Is during the growing season for the 1, 2 and 3 months accumulation periods. A forward stepwise procedure was used for the multiple regression modelling. The model started with only one (the highest explaining) variable and adds more variables if the significance stays below the 0.05 (criterion one of stepping method) and the coefficient of determination (R^2) keeps on increasing meanwhile. However, if the combination of more variables made the significance increase up to 0.10 (criterion two of stepping method) the variable was excluded from the model. After running the model it was inspected for multicollinearity between variables by the use of the variance inflated factor (VIF) (Ott and Longnecker, 2008):

$$VIF = \frac{1}{1-R^2} \tag{5}$$

where the denominator in Equation 5 equals the tolerance (T). Variables exceeding a coefficient of determination (R^2) equal to 0.67 (high correlation between two SP(E)Is) were excluded from the model. Equation 5 shows that this holds VIF ≥ 3.

To produce simple models it was decided to include not more than five variables. In case of an excess of variables the following criterion was applied: variables were excluded from the model if the R^2 decreases relatively less than the Bayesian Information Criteria (BIC) (Schwarz, 1978) increases. The BIC was preferred over an almost similar criterion AIC (Akaike Information Criteria), regarding that the BIC performs better when a lot of observations are included in the model.

Concerning raw crop yield data, being significant with climate regions and NUTS2, the modelling followed a different approach based on linear mixed effect models. This procedure enables to separate variables into fixed effects, common across the entire model (such as SP(E)Is or climate regions) and random effects, which account for unexplained differences between NUTS2 regions. In this way the model controls for differences across NUTS2 regions, while isolating the common effect of drought on crop changes (SPSS Inc., 2005). The models were run under three different scenarios: i) no accounting in differences between NUTS2, ii) NUTS2 as random factor, and iii) NUTS2 as random factor and climate regions as fixed affect.

The models give an expression for crop yield losses (i.e. negative change) due to water scarcity or surplus (see Equation 6). Every variable ($SP(E)I_{accu\_month}$) is multiplied by the slope b_n, which denotes the contribution of crop yield loss. The example model in Equation 7 has only two variables included. In the 2 months aggregated period in April (SPI2_4) big crop yield losses could be expected due to water surplus (noted by a negative sign in the slope) and a less strong, but still significant, correlation in May, June and July (SPI3_7) due to water scarcity (positive slope). The crops barley, wheat and sugar beet may include some months of the previous year within their growing season ((September), October, November and December). In this case variables include the letter P (from 'previous'), e.g. SPEI2_11_P.

$$Y' = b_1 \times \mathbf{SP(E)I_{accu\_month}} + b_2 \times \mathbf{SP(E)I_{accu\_month}} \tag{6}$$

$$Y'_{example} = -5{,}827 \times \mathbf{SPI2\_4} + 2{,}408 \times \mathbf{SPI3\_7} \tag{7}$$

The modelling procedure for de-trended data was done for i) Europe and ii) the three climate regions that account for most of the data: Atlantic, Continental and Mediterranean. Mind that in the example of Equation 7 the calculated SPI-values of an individual NUTS2 region should be filled in and not the average of the SPIs over Europe or a climate region.

3 Results

The chapter starts with the outcomes of detecting the best moving average de-trended period, which was not necessary for de-trending using linear regression. For linear regression however, it has to be investigated how many NUTS2 regions had a significant regression line and could be included in the statistical models. Next, information is presented to investigate correlations, including;

- Effects of the difference between the two crop de-trending methods of crop yield data
- Effects of drought indices accumulation periods
- The difference between SPI and SPEI
- Correlations for different scales and regions within Europe

3.1 De-trending crop yield data

3.1.1 Detection moving average de-trending period

The results of the partial autocorrelation function (PACF, see section 2.4.2) show that for most crops a period of one year (lag 1) before (and after) is considered to be the best de-trending period (Figure 15) and that for a lot of NUTS2 regions it was even advised not to de-trend at all (not significant). For approximately 5% of the NUTS2 regions two (or three) years were suggested using PACF. Therefore the best de-trending period to be further investigated were in the range of one and two years before (and after) including: Ano_1B, Ano_1B_%, Ano_1B_A, Ano_1B_A_%, Ano_2B, Ano_2B_%, Ano_2B_A and Ano_1B_A_% (for explanation of acronyms, see section 2.4.2).

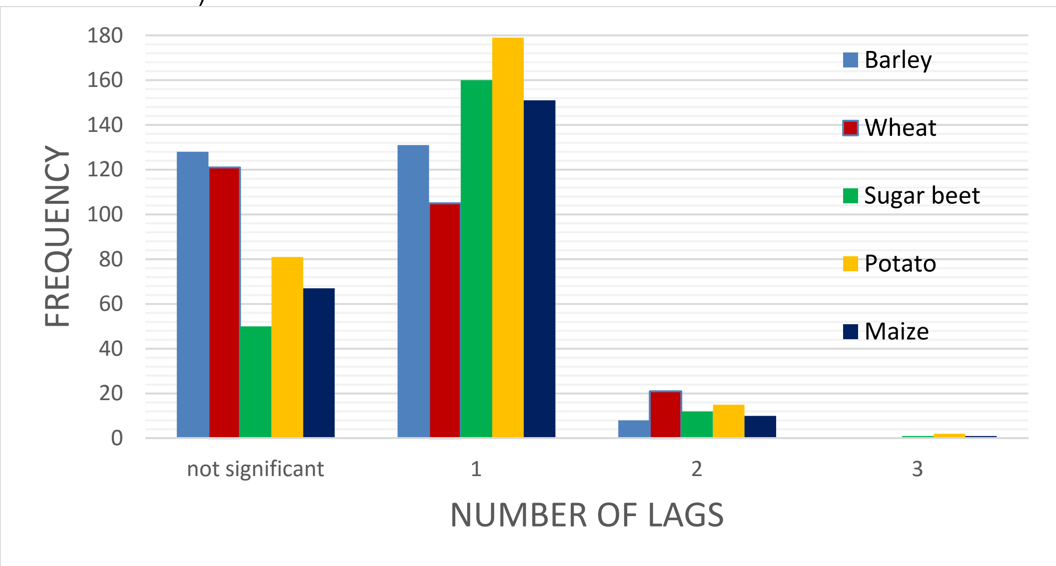

Figure 15: Distribution of NUTS2 regions according to the number of lags, as a suggested length for the moving average period for all five crop yield using the PACF. Most data give zero (not significant) or only one year (lag 1) of autocorrelation. Sugar beet, potato and maize are the only crops that include one or two NUTS2 regions in the lag 3 category.

In the next step eight possible combinations of crop yield anomaly calculations within the mentioned range were correlated (Spearman R) with the drought indices. To correct for positive and negative corrections, every individual NUTS2 outcome was: i) squared (R^2) and ii) transformed into positive numbers by taking the absolute number (|R|). R^2 gives more focus to higher individual correlations than the |R|. Since comparing the moving average method with the linear regression method is easier if the units are the same; anomalies expressed as percentage is preferred over non-percentage (criterion 1). In addition, a simpler model is ideal, hence periods only including past-data (B) are preferred over past-and-future-data (B_A) (criterion 2).

Table 4, showing the highest and second highest average score of the best de-trending moving average period, reveals that the periods are unequal for all crops. Concerning the criteria 1 and 2, barley and wheat have period Ano_2B_A_% in common in their two highest scores. For sugar beet, potato and maize the simpler period of Ano_2B_% will be used for following analysis.

Table 4: Best de-trending using the moving average method based on the number one (1st) and number two (2nd) highest average European correlations between crop yield anomalies and drought indices. Two procedures of correlating are established: R^2 and |R|. Looking at the periods they have in common, where 'percentage' is preferred over 'non-percentage', both procedures indicate that the anomaly two years before and after percentage (Ano_2B_A_%) gives the highest score for barley and wheat and the anomaly of the two years before percentage (Ano_2B_%) for sugar beet, potato and maize

Crop	Best de-trending moving average period			
	$R^2{}_{1st}$	$R^2{}_{2nd}$	$\lvert R\rvert_{1st}$	$\lvert R\rvert_{2nd}$
Barley	Ano_2B	Ano_2B_A	**Ano_2B_A_%**	Ano_2B_A
Wheat	Ano_2B_A	**Ano_2B_A_%**	Ano_2B_A	**Ano_2B_A_%**
Sugar beet	**Ano_2B_%**	Ano_1B_%	**Ano_2B_%**	Ano_1B_%
Potato	Ano_2B	**Ano_2B_%**	Ano_2B	**Ano_2B_%**
Maize	**Ano_2B_%**	Ano_1B	**Ano_2B_%**	Ano_1B

3.1.2 Data availability in the linear regression de-trending method

Since not all data series met the conditions of 0.1% significance linear regression some NUTS2 regions had to be excluded for analysis, in contrast to what has been done for the moving average method. Sugar beet and barley lost most regions with 32 % and 39 % respectively of data still left compared to moving average. Potato and maize lost relatively the least, including still 69 % and 65 % of the data and wheat lost about half of its data (51 % left).

3.2 Correlations between crop yield anomalies and drought indices

Linkages ($p \leq 0.05$) have been found between crop yield anomalies and the drought index SPI for the de-trending method moving average (Tables 5 – 9) and linear regression (Tables 10 – 14). The moving average de-trending method gave about the same models as linear regression, in which not exact the same variables appeared in the formulas, but the contribution (slope b) of the predictor (i.e. $SP(E)I_{accu\_month}$) to the model are likewise per part of the growing season (will be discussed later on in more detail).

Both de-trended data sets have been correlated with the SPEI as well, Tables A51 – A510. Concluded was that SPEI performs with nearly equivalent results, although not the exact same variables contributed to the models. Moreover, according to Figure 16 the correlations (R^2) for the moving average de-trended were barely higher for SPEI than SPI and even much lower for the linear regression de-trended data set. The correlations were, although significant, low and did not exceed the value of 0.2.
Concerning the results of the raw data, after some try outs it was clear that the raw data gave extreme low correlations and hardly included one or more variables in a significant model. For this reason raw data was excluded from further analysis.

Table 5: Statistical yield change model that describes the relationship between the barley yield anomaly and the SPI for the moving average de-trended data set

Scale	Statistical model	R^2	N
Europe	2,827 x **SPI3_7** + 2,408 x **SPI2_4** - 1,852 x **SPI1_12_P** - 1,044 x **SPI1_8** - 0,874 x **SPI3_9_P**	0.027	3631
Atlantic	-4,597 x **SPI3_6** + 5,281 x **SPI1_11_P** - 2,608 x **SPI3_1** + 1,106 x **SPI1_3**	0.117	1013
Continental	2,839 x **SPI2_7** - 1,617 x **SPI2_12_P** + 1,377 x **SPI1_4**	0.069	1115
Mediterranean	6,797 x **SPI3_3** + 6,709 x **SPI3_6** - 3,485 x **SPI1_8**	0.075	1016

Table 6: Statistical yield change model that describes the relationship between the wheat yield anomaly and the SPI for the moving average de-trended data set

Scale	Statistical model	R^2	N
Europe	3,004 x **SPI2_4** - 2,35 x **SPI2_9_P** - 1,605 x **SPI1_12_P** + 0,838 x **SPI2_7**	0.036	3432
Atlantic	-5,332 x **SPI3_12_P** - 2,347 x **SPI3_7** - 1,52 x **SPI3_9_P**	0.182	994
Continental	-4,002 x **SPI3_10_P** + 2,908 x **SPI3_7** + 2,15 x **SPI3_3**	0.056	1105
Mediterranean	10,019 x **SPI3_5** + 2,825 x **SPI2_2** + 2,195 x **SPI1_10_P**	0.133	941

Table 7: Statistical yield change model that describes the relationship between the sugar beet yield anomaly and the SPI for the moving average de-trended data set

Scale	Statistical model	R^2	N
Europe	No significant model	-	2748
Atlantic	-7,355 x **SPI2_5**	0.008	812
Continental	4,911 x **SPI3_8** - 2,534 x **SPI1_3** - 2,824 x **SPI2_1**	0.030	928
Mediterranean	-8,105 x **SPI1_1** + 6,593 x **SPI2_5**	0.016	684

Table 8: Statistical yield change model that describes the relationship between the potato yield anomaly and the SPI for the moving average de-trended data set

Scale	Statistical model	R^2	N
Europe	2,726 x **SPI3_8** - 2,664 x **SPI2_4** - 1,92 **x SPI1_10**	0.027	3826
Atlantic	5,575 x **SPI1_4** + 3,222 x **SPI1_8** - 3,621 x **SPI2_10**	0.071	1103
Continental	-5,326 x **SPI2_4** + 5,695 x **SPI3_10** - 5,39 x **SPI1_10** + 2,4 x **SPI1_7**	0.066	1054
Mediterranean	2,71 x **SPI1_3** - 2,41 x **SPI1_10** + 1,936 x **SPI3_8**	0.039	1121

Table 9: Statistical yield change model that describes the relationship between the maize yield anomaly and the SPI for the moving average de-trended data set

Scale	Statistical model	R^2	N
Europe	8,812 x **SPI2_7** - 9,395 x **SPI2_10**	0.003	2835
Atlantic	-11,805 x **SPI2_4** + 7,605 x **SPI1_7**	0.026	766
Continental	25,105 x **SPI1_6**	0.004	765
Mediterranean	-12,433 x **SPI1_10**	0.009	1038

Table 10: Statistical yield change model that describes the relationship between the barley yield anomaly and the SPI for the linear regression de-trended data set

Scale	Statistical model	R^2	N
Europe	2,013 x **SPI2_4** + 3,18 x **SPI1_11_P** + 2,175 x **SPI2_3**	0.018	1424
Atlantic	8,921 x **SPI3_9_P** - 8,077 x **SPI1_9_P** + 3,05 x **SPI2_8**	0.062	558
Continental	-2,754 x **SPI2_12_P** - 2,889 x **SPI3_2** + 2,46 x **SPI3_6**	0.062	361
Mediterranean	5,98 x **SPI3_12_P** + 6,661 x **SPI1_4** + 5,741 x **SPI3_3** -5,602 x **SPI1_8** + 5,665 x **SPI1_5**	0.138	426

Table 11: Statistical yield change model that describes the relationship between the wheat yield anomaly and the SPI for the linear regression de-trended data set

Scale	Statistical model	R^2	N
Europe	-5,367 x **SPI3_12_P**	0.008	1742
Atlantic	-7,115 x **SPI3_12_P** - 3,29 x **SPI3_9_P** - 2,744 x **SPI1_6** + 2,429 x **SPI1_4**	0.095	807
Continental	-4,744 x **SPI2_11_P** - 1,765 x **SPI2_9_P** - 1,361 x **SPI2_4**	0.109	498
Mediterranean	No significant model	-	283

Table 12: Statistical yield change model that describes the relationship between the sugar beet yield anomaly and the SPI for the linear regression de-trended data set

Scale	Statistical model	R^2	N
Europe	No significant model	-	877
Atlantic	No significant model	-	292
Continental	No significant model	-	305
Mediterranean	537,394 x **SPI2_4**	0.021	197

Table 13: Statistical yield change model that describes the relationship between the potato yield anomaly and the SPI for the linear regression de-trended data set

Scale	Statistical model	R^2	N
Europe	7,198 x **SPI2_8** + 4,993 x **SPI1_3** - 4,755 x **SPI1_4** - 3,369 x **SPI2_7**	0.034	2642
Atlantic	5,856 x **SPI1_8** + 13,586 x **SPI1_3** - 7,326 x **SPI3_5** - 6,724 x **SPI2_4**	0.042	771
Continental	15,632 x **SPI2_8** + 7,259 x **SPI1_3** - 6,4 x **SPI2_7**	0.051	808
Mediterranean	-3,195 x **SPI2_10** + 3,34 x **SPI1_3**	0.022	699

Table 14: Statistical yield change model that describes the relationship between the maize yield anomaly and the SPI for the linear regression de-trended data set

Scale	Statistical model	R^2	N
Europe	No significant model	-	1839
Atlantic	15,406 x **SPI2_8**	0.013	557
Continental	18,379 x **SPI1_9**	0.007	661
Mediterranean	6,679 x **SPI3_3**	0.018	516

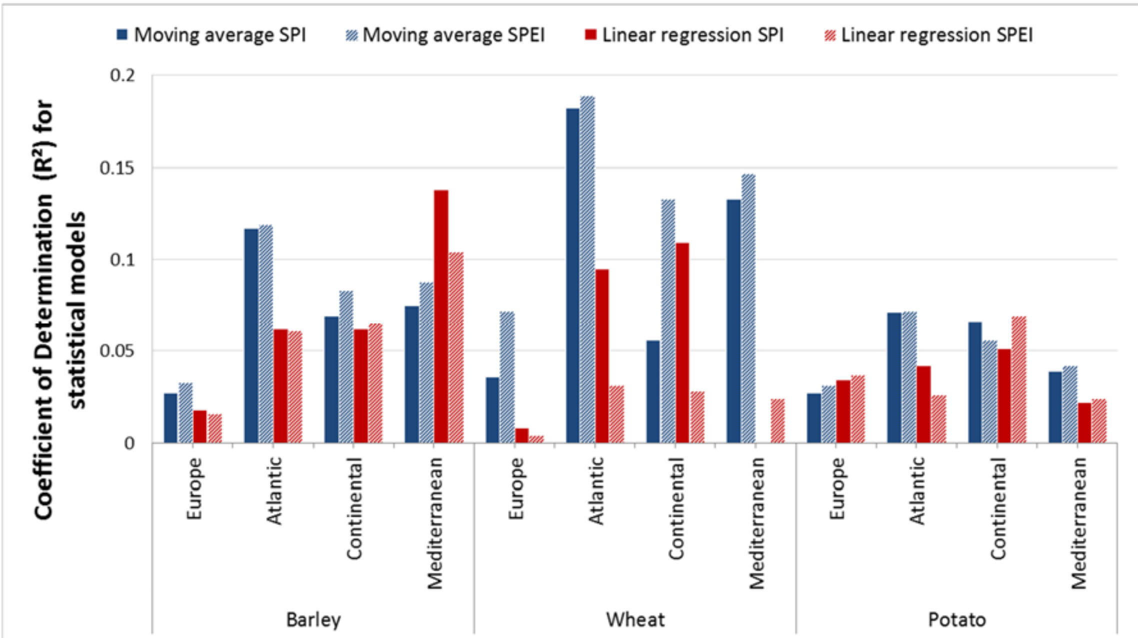

Figure 16: Coefficient of Determination (R^2) of the statistical models for barley, wheat and potato (the three crops with the highest correlation in the statistical models) for the moving average de-trending method (blue) and the linear regression de-trending method (red). The table indicates that the correlations with SPEI (dashed) is not always higher than with SPI (solid), moreover for linear regression SPEI usually performs worse.

Figure 17 provides an overview[4] of the correlation range that have been found for individual NUTS2 regions (SPI1, 2, 3 and 6 for the moving average de-trending method), which gives the average (orange), 25-75 percent interval (dark blue) and 10-90 percent interval (light blue). Mind

[4] Figure 17 – Figure 25 have a chart type set as line, although the series are not continuous data. The lines however make it easier to see links between the previous and upcoming months.

that the average coefficients found in Figure 16 are indicated in R^2, while the individual correlation range is given in R.

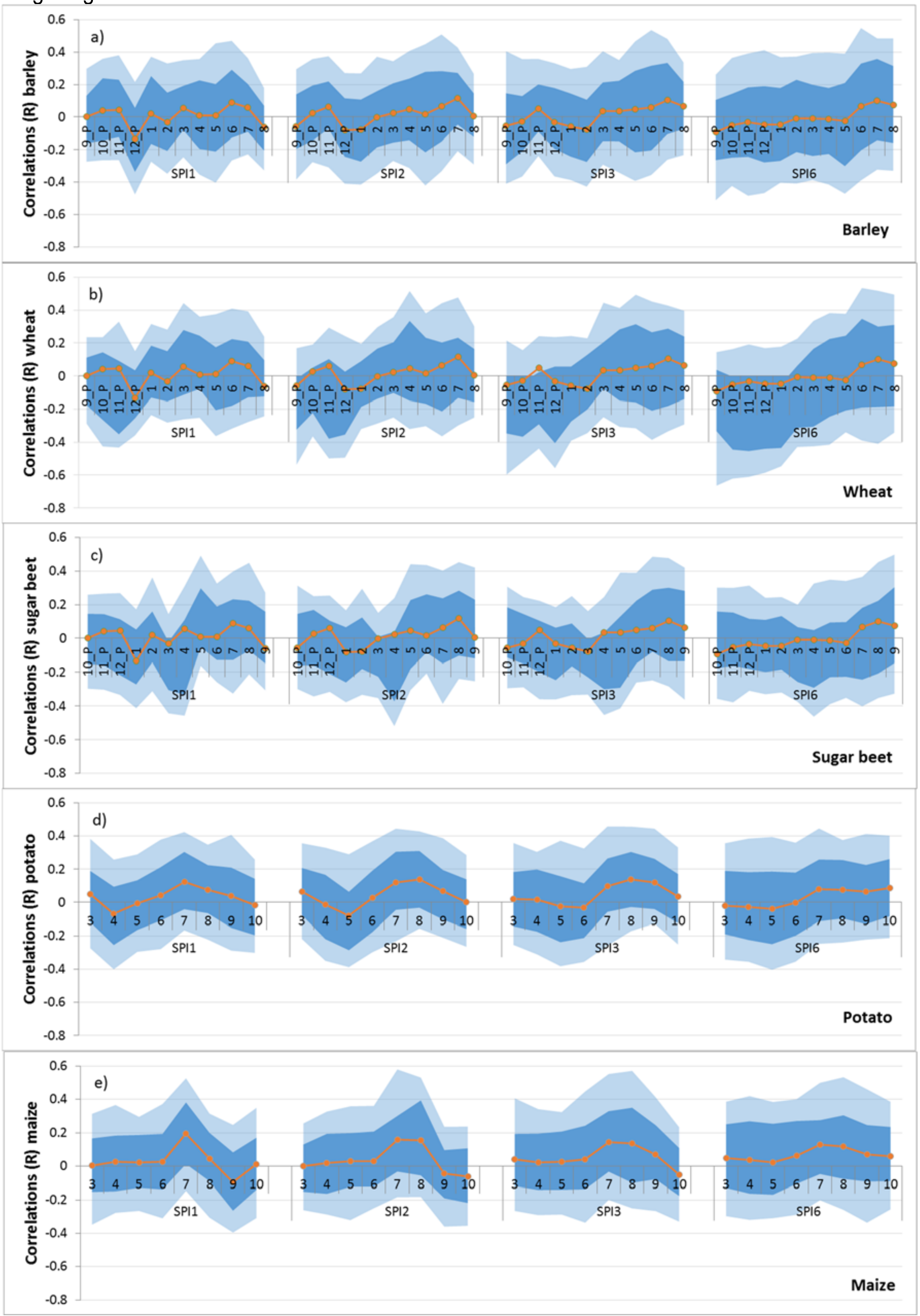

Figure 17: Correlation range (R) for SPI1, 2, 3 and 6 in the moving average de-trending method for individual NUTS2 regions. The graphs provide the average (orange), 25-75 percent interval (dark blue) and 10-90 percent interval (light blue).

The statistical models in Tables 5 – 14 and A51 – A510 only use SP(E)Is for the significant part of the growing season. More details on the difference between SPI and SPEI can be studied when investigating the whole growing season. Figures 18 and 19 demonstrate that only barley, wheat and potato have higher correlations for SPEI during the latest stage of the growing season on Pan-European scale. The stars in the graphs indicate the variables for the SPI that were included in the significant model using the moving average de-trending method (Tables 5 – 9).

If we focus only on barley and potato per climate region (Atlantic, Continental and Mediterranean) we find in Figures 20 and 21 that the Continental Climate region is the main factor for the difference on the European scale. The Atlantic and Mediterranean climates barely show higher correlations for SPEI.

Figures 18 and 19 were expanded to the three climate regions in Figures 22 and 23 for SPI. The five crops all give unique relations for the SPIs in drought (and wet spells) response per region. Most variations in climate regions are found for barley and wheat. Although the crops show a lot of regional differences, the crops itself have most of the drought response in common. The similarity of barley and wheat are confirmed once more with a strong positive relation at the end of the growing season between crop yield anomalies and SPI6 (Figure 24). Negative correlations dominate in the start of the growing season of wheat, of which the Atlantic Climate region plays a dominant role.

Potato and maize follow the same drought response pattern as well (Figure 25), with a low correlation from March till June and thereafter increase. Since the SPI6 covers large part of the growing season this accumulation period gives a comprehensive summary of the whole growing season. However, in case of strong variations between positive and negative correlations between SPIs and SPEIs over shorter periods and crop yield anomalies the result is visualised as a straight line with fluctuations around zero. The pattern of sugar beet is therefore not well visible in the SPI6.

As a final result the correlations between the drought indices and crop yield anomalies were subdivided over five parts of the growing season (i.e.: sowing, early growing season, mid growing season/flowering, late flowering and harvest). Figures 26 – 30 show that, even though the linear regression de-trending method is high limited to a small amount of data, the contributions to the models (slope b) between SPI and crop yield anomalies are well visible for barley, wheat and potato. Some contraries exist, e.g. in the sowing period and mid stage in the growing season of potato.

The best explaining accumulation period for barley and wheat was SPI3, of which the result was more clear for wheat than for barley. For the other three crops SPI1 and 2 contributed most to the statistical models. No best accumulation periods for the regions Europe, Atlantic Climate region and Continental Climate region have been found. For the Mediterranean area SPI1 was most common in the statistical models.

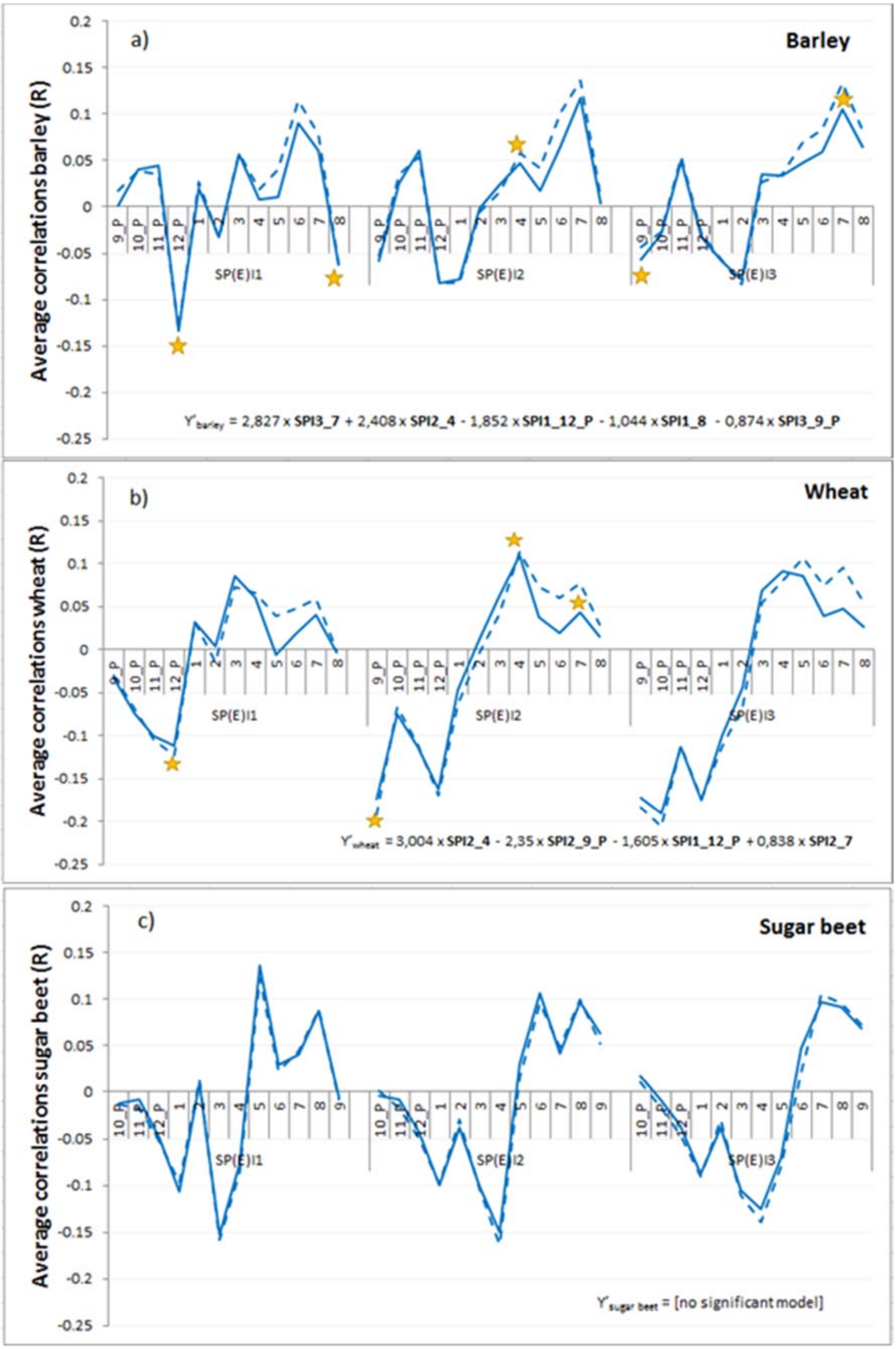

Figure 18: Average Pearson correlation (R), between European crop yield anomalies and drought indices SPI (solid line) and SPEI (dashed line) for accumulation periods of 1, 2 and 3 months for barley (a), wheat (b) and sugar beet (c), The stars indicate a significant predictor variable included in the statistical model with p ≤0.05 (see Tables 5 – 7. For potato and maize: see next page.

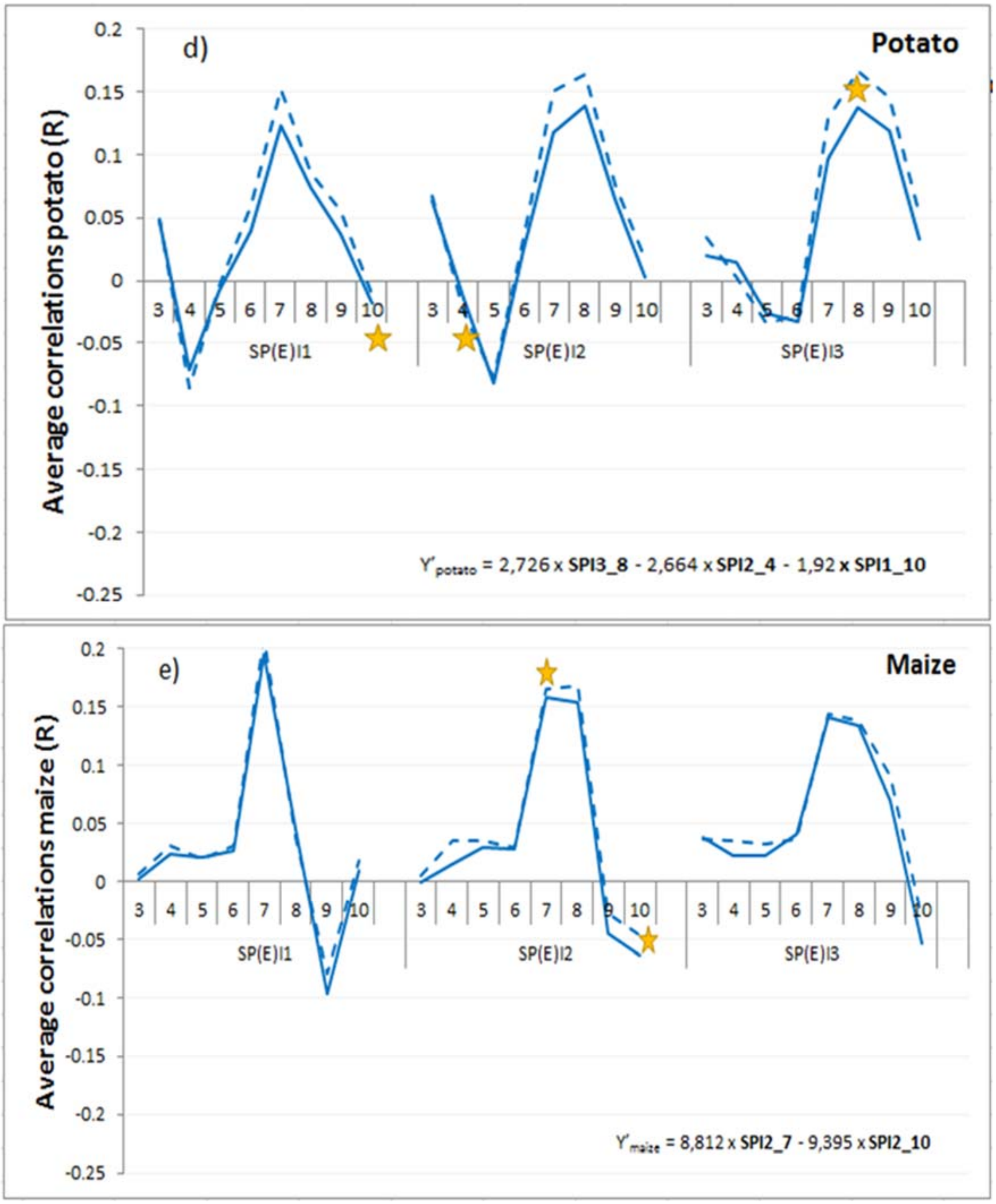

Figure 19: Average Pearson correlation (R), between European crop yield anomalies and drought indices SPI (solid line) and SPEI (dashed line) for accumulation periods of 1, 2 and 3 months for potato (d) and maize (e). The stars indicate a significant predictor variable included in the model with p ≤0.05 (see Tables 8 and 9).

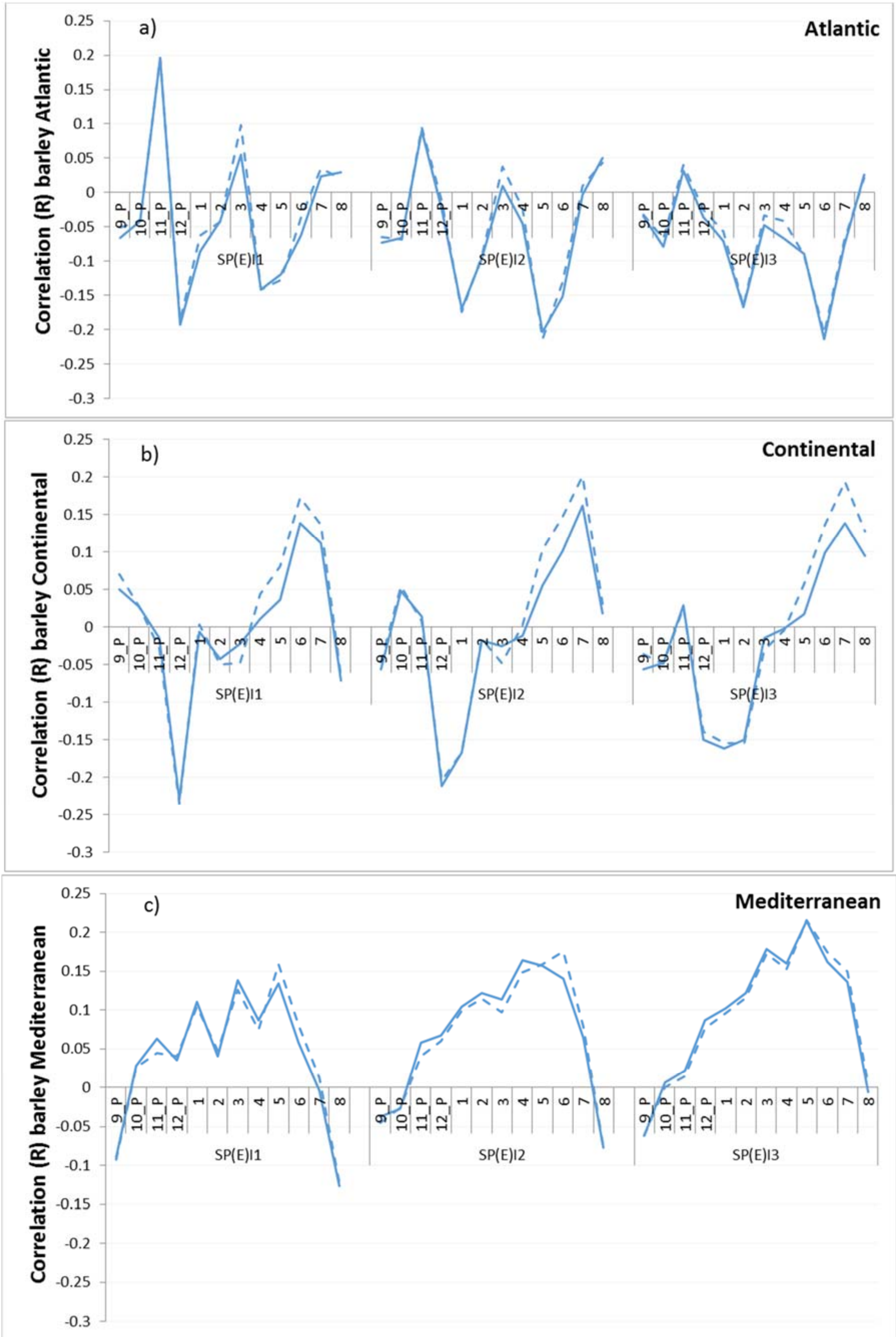

Figure 20: Correlation (R) of barley yield anomalies and drought indices SPI (solid line) and SPEI (dashed line) for the largest climate regions: Atlantic (a), Continental (b) and Mediterranean (c). Only for the Continental Climate region a stronger correlation for SPEI is noticed during the flowering period of the growing season.

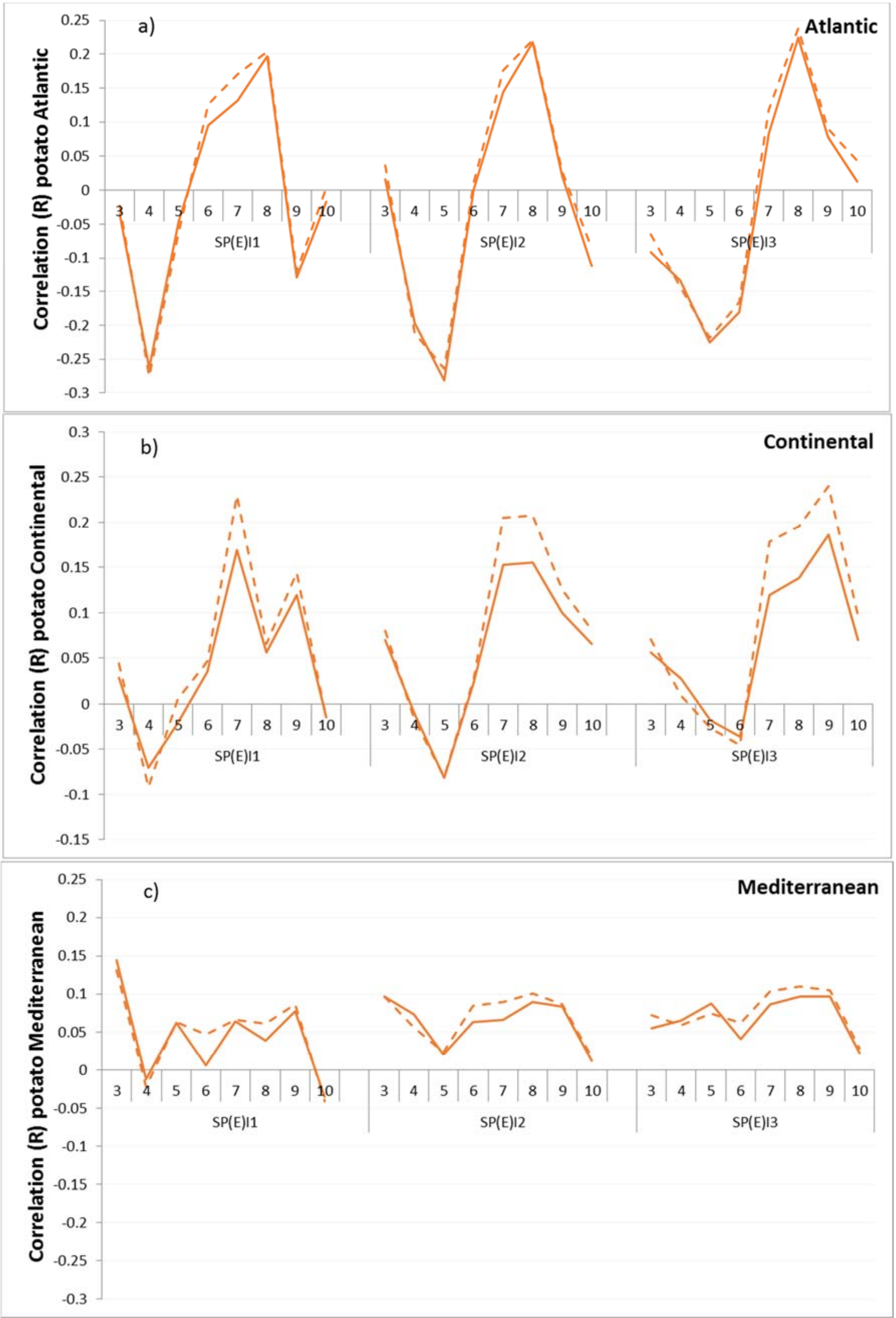

Figure 21: Correlation (R) of potato yield anomalies and drought indices SPI (solid line) and SPEI (dashed line) for the largest climate regions: Atlantic (a), Continental (b) and Mediterranean (c). Just like for barley, the Continental Climate is the only region showing a higher significance for SPEI than SPI.

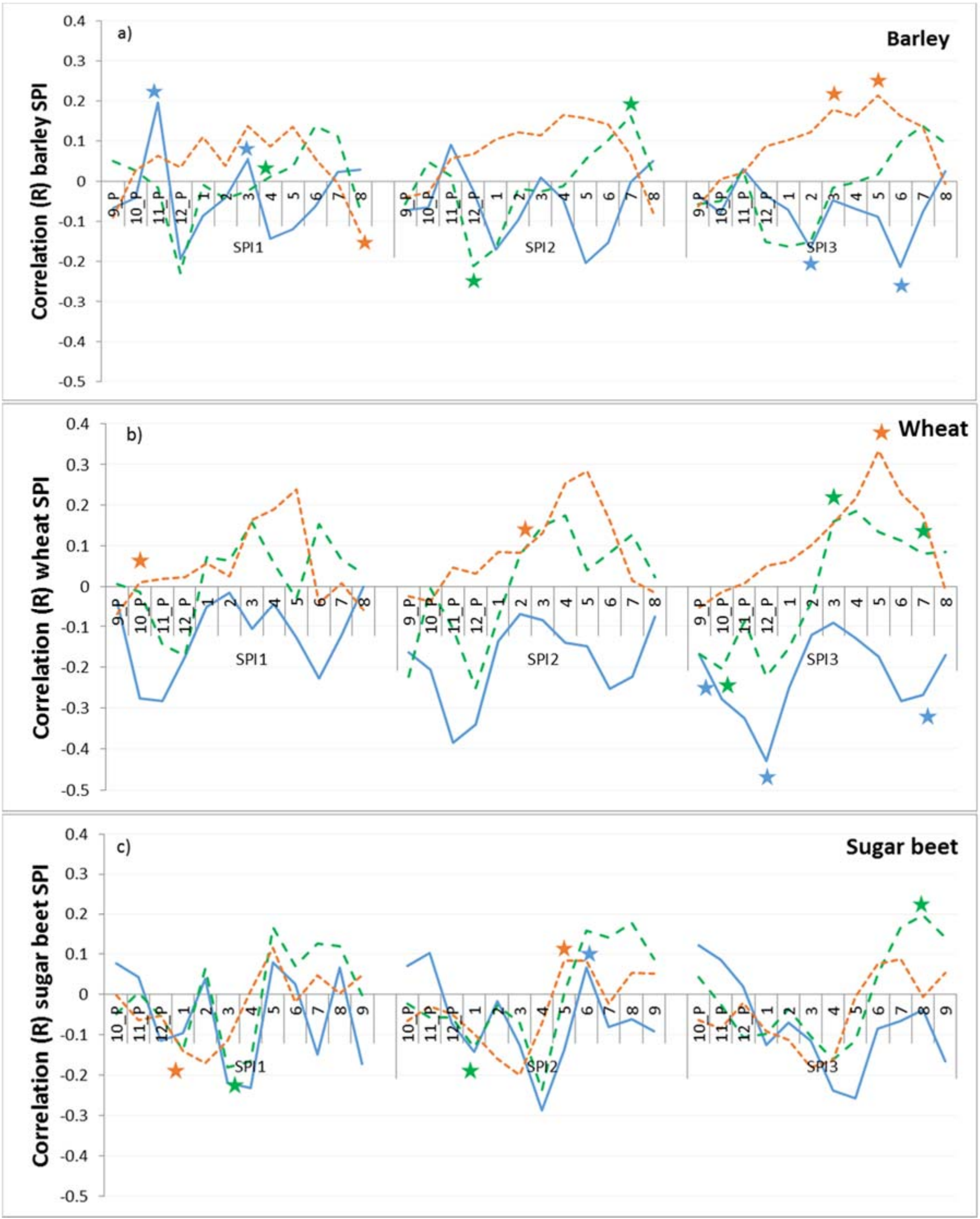

Figure 22: Average Pearson correlation (R), between SPIs 1, 2 and 3 and crop yield anomalies by moving average de-trending method in climate regions Atlantic (blue solid line), Continental (green dashed line) and Mediterranean (orange dotted line) for barley (a), wheat (b) and sugar beet (c). The stars indicate a significant predictor variable included in the statistical model with p ≤0.05 (Tables 5 – 7) . See next page for potato and maize.

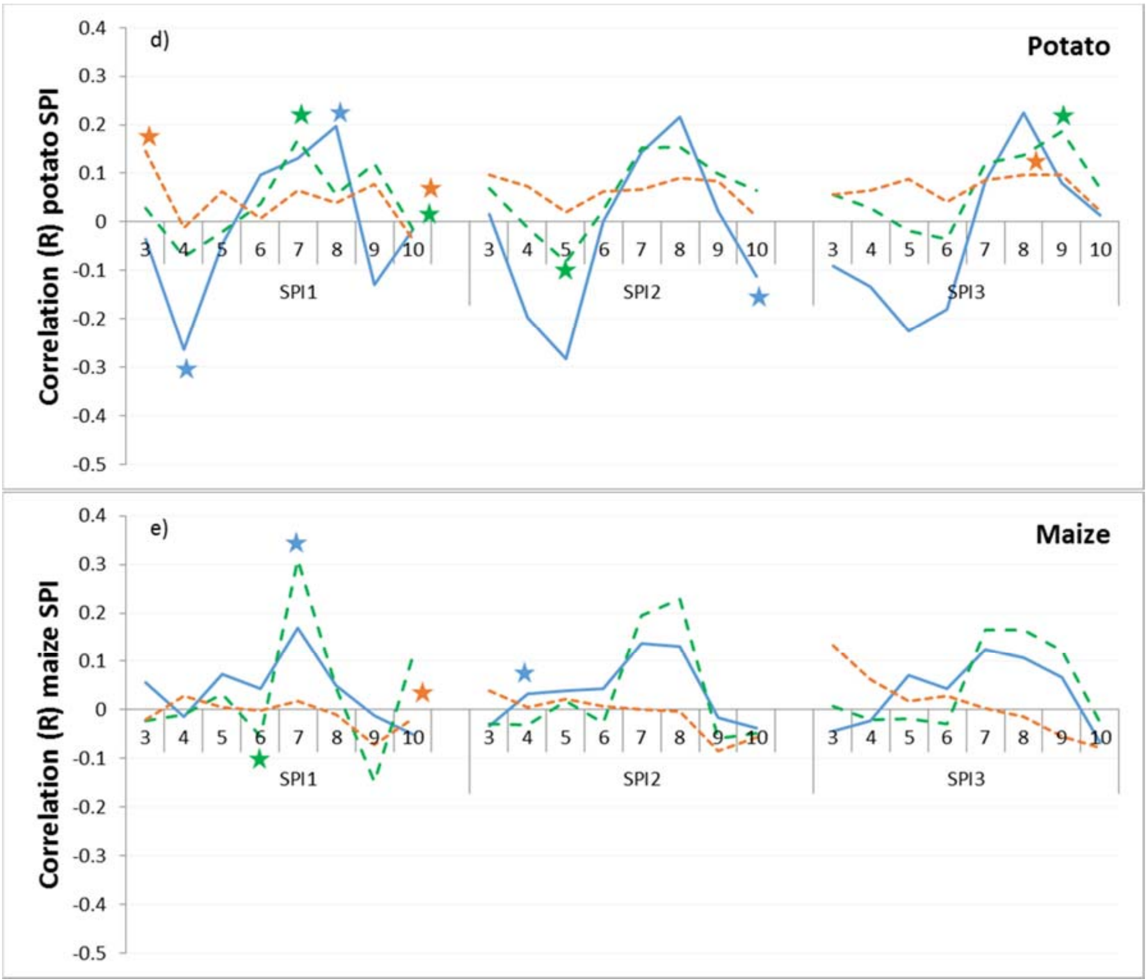

Figure 23: Average Pearson correlation (R), between SPIs 1, 2 and 3 and crop yield anomalies by moving average de-trending method in climate regions Atlantic (blue solid line), Continental (green dashed line) and Mediterranean (orange dotted line) for potato (d) and maize (e). The stars indicate a significant predictor variable included in the statistical model with p ≤0.05 (Tables 8 and 9).

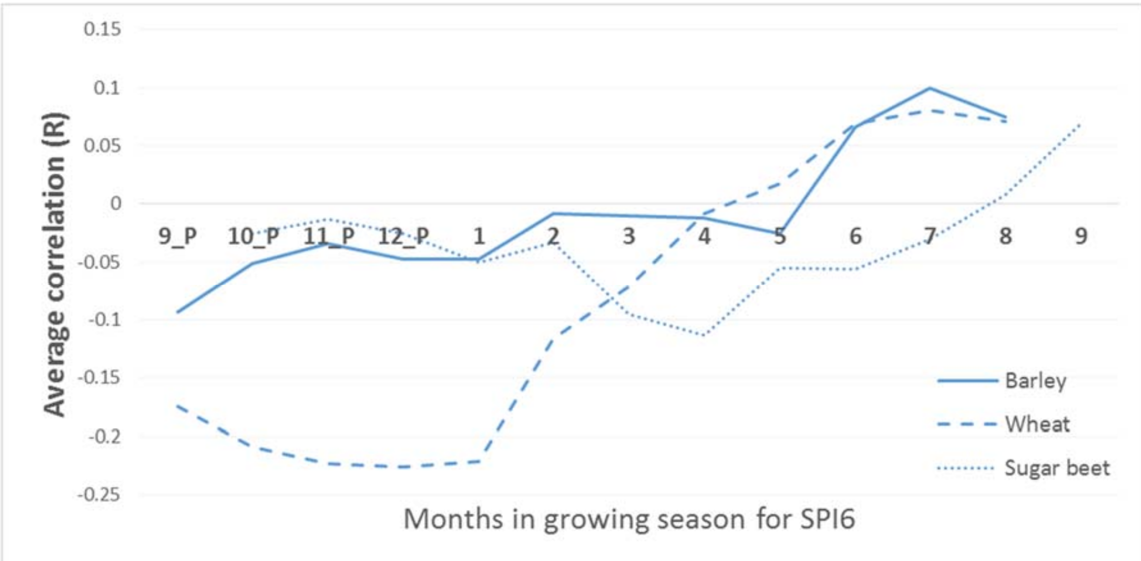

Figure 24: Average pan-European correlation (R) between crop yield anomalies and SPI6 using the moving average de-trended crop yield data for barley, wheat and sugar beet. The similarity of a positive correlation of barley and wheat is well visible at the flowering and harvesting period. From September to January, negative relations dominate in the wheat growing season.

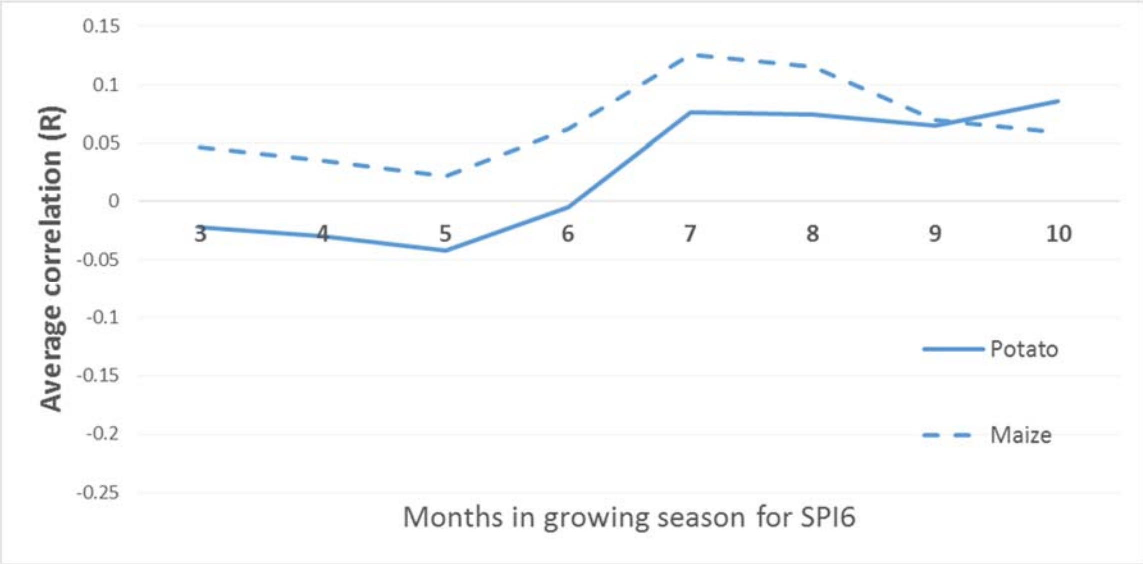

Figure 25: Correlations European moving average de-trended crop yield data for potato and maize with the SPI6. Starting from July, a positive correlation is visible for both crops.

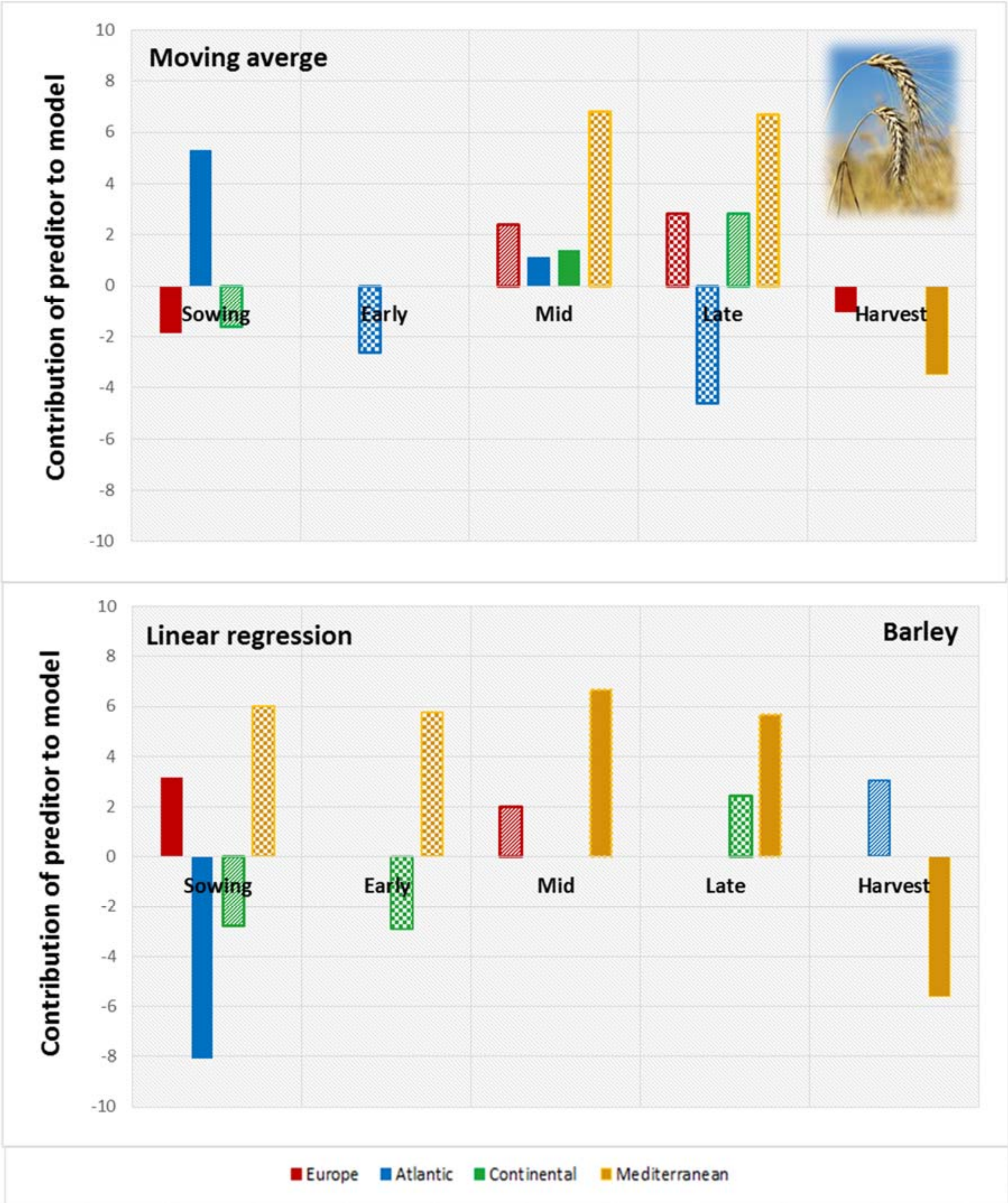

Figure 26: Contribution of predictor (slope b) to SPI models for Europe (red), Atlantic (blue), Continental (green) and Mediterranean Climate regions (yellow) divided over five parts of the growing season for barley. Here the three accumulation periods are indicated as: 1 (solid), 2 (striped) and 3 (blocked). Positive contribution refers to losses by drier than average periods (or droughts) and a negative contribution suggest crop yield losses in case of higher than normal precipitation. The arrows indicate a larger than within the range [-10 – 10] contribution. For a complete overview of the statistical model, conduct Tables 5 and 10.

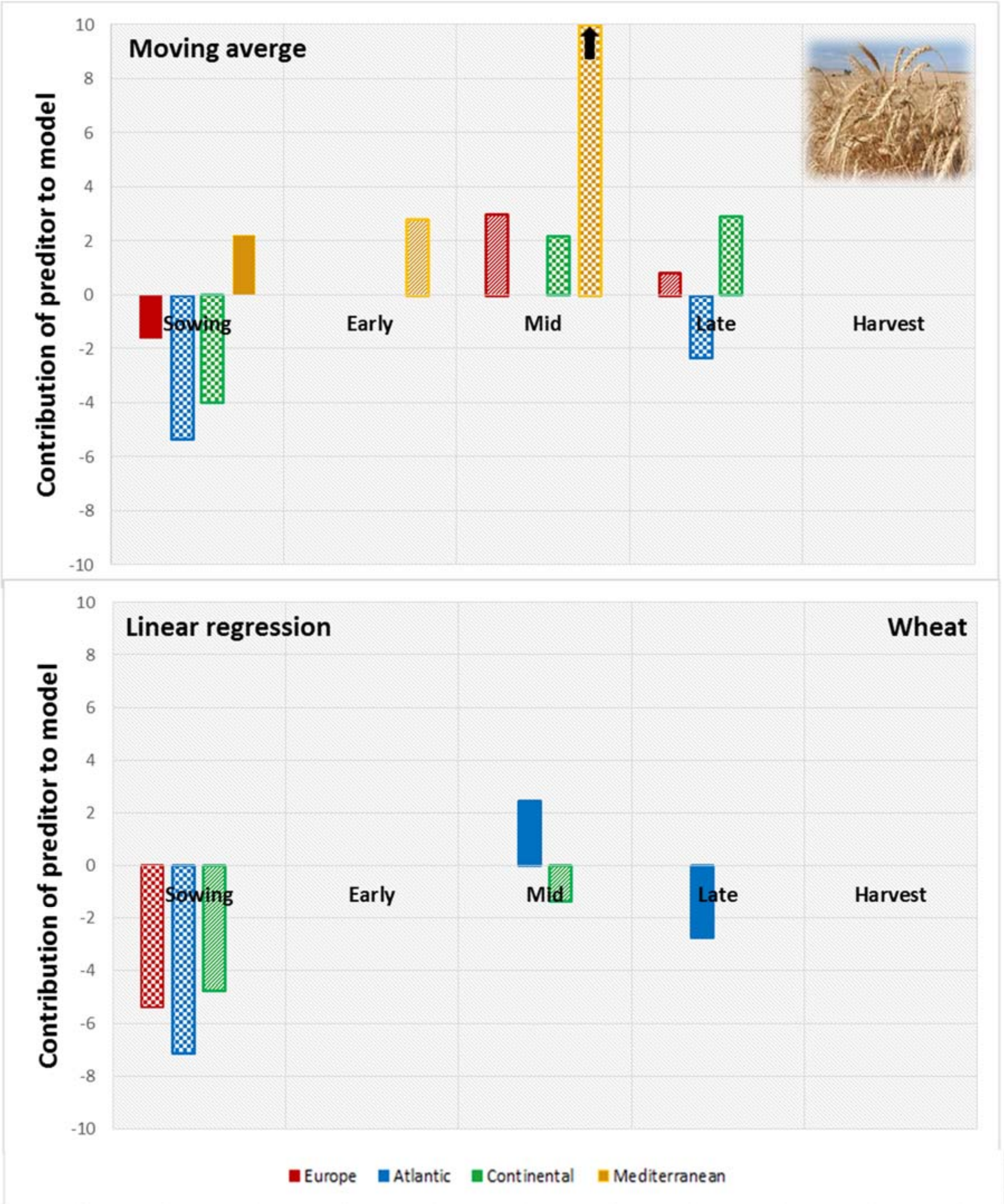

Figure 27: Contribution of predictor (slope b) to SPI models for Europe (red), Atlantic (blue), Continental (green) and Mediterranean Climate regions (yellow) divided over five parts of the growing season for wheat. Here the three accumulation periods are indicated as: 1 (solid), 2 (striped) and 3 (blocked). Positive contribution refers to losses by drier than average periods (or droughts) and a negative contribution suggest crop yield losses in case of higher than normal precipitation. The arrows indicate a larger than within the range [-10 – 10] contribution. For a complete overview of the statistical model, conduct Tables 6 and 11.

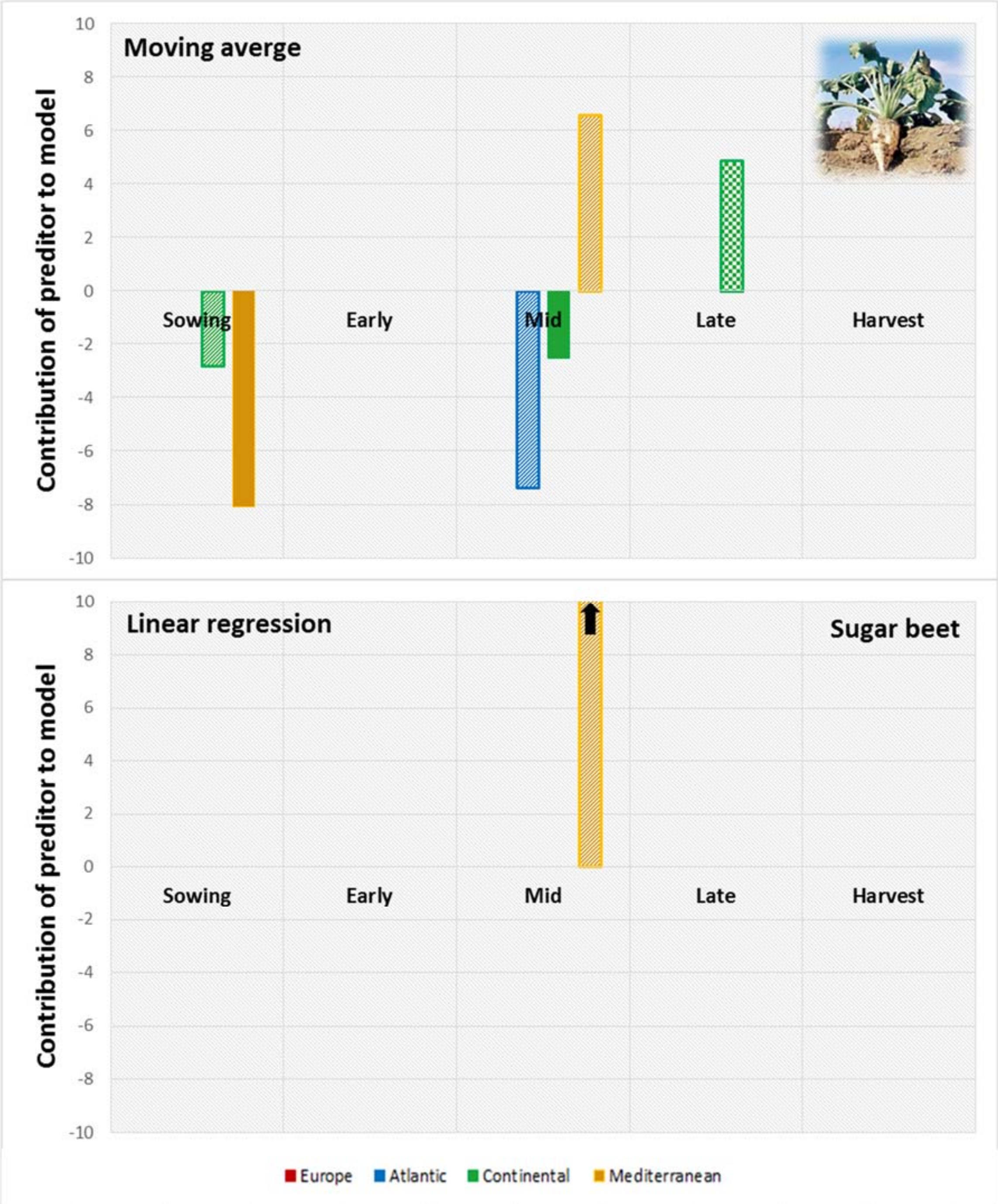

Figure 28: Contribution of predictor (slope b) to SPI models for Europe (red), Atlantic (blue), Continental (green) and Mediterranean Climate regions (yellow) divided over five parts of the growing season for sugar beet. Here the three accumulation periods are indicated as: 1 (solid), 2 (striped) and 3 (blocked). Positive contribution refers to losses by drier than average periods (or droughts) and a negative contribution suggest crop yield losses in case of higher than normal precipitation. The arrows indicate a larger than within the range [-10 – 10] contribution. For a complete overview of the statistical model, conduct Tables 7 and 12.

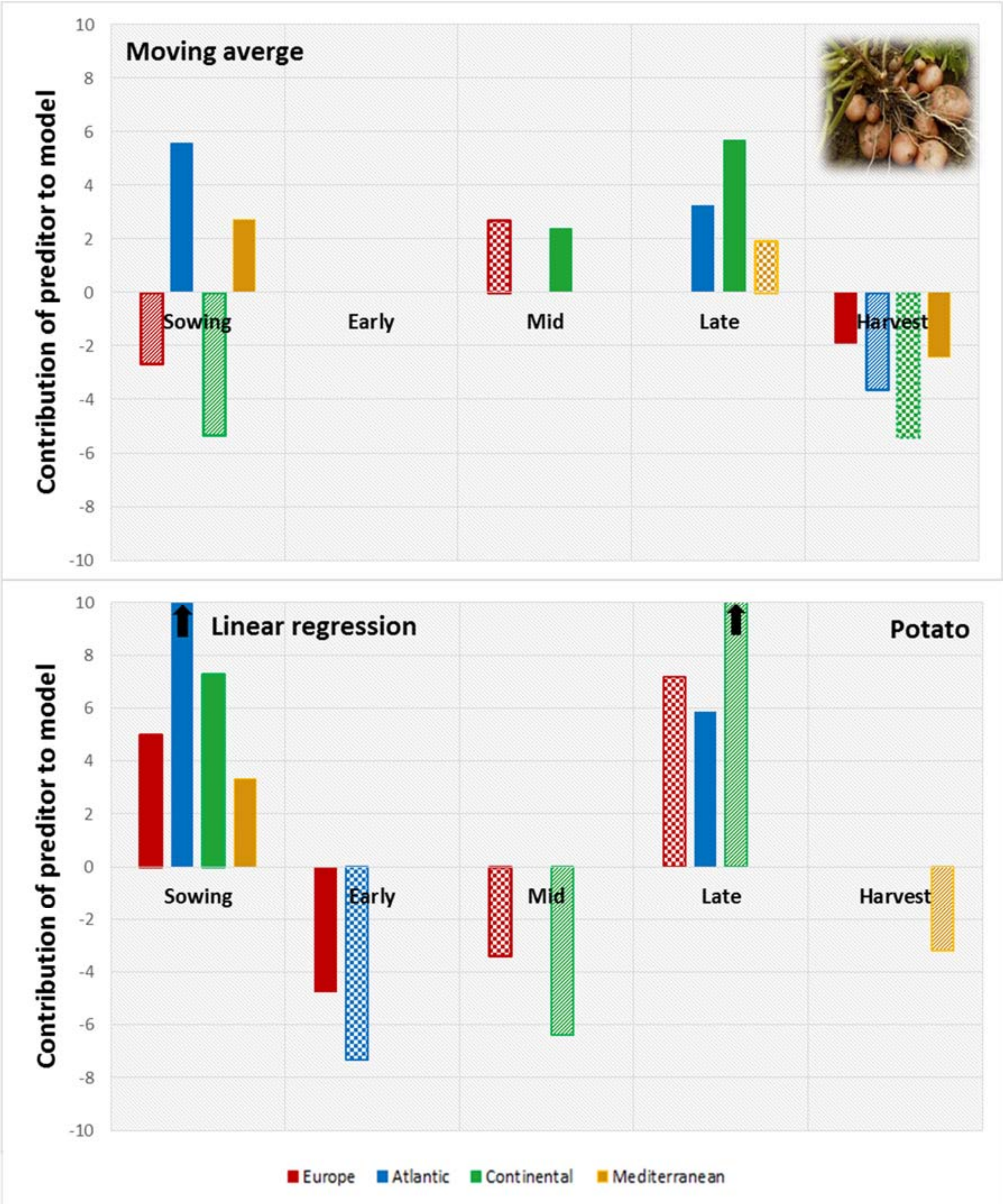

Figure 29: Contribution of predictor (slope b) to SPI models for Europe (red), Atlantic (blue), Continental (green) and Mediterranean Climate regions (yellow) divided over five parts of the growing season for potato. Here the three accumulation periods are indicated as: 1 (solid), 2 (striped) and 3 (blocked). Positive contribution refers to losses by drier than average periods (or droughts) and a negative contribution suggest crop yield losses in case of higher than normal precipitation. The arrows indicate a larger than within the range [-10 – 10] contribution. For a complete overview of the statistical model, conduct Tables 8 and 13.

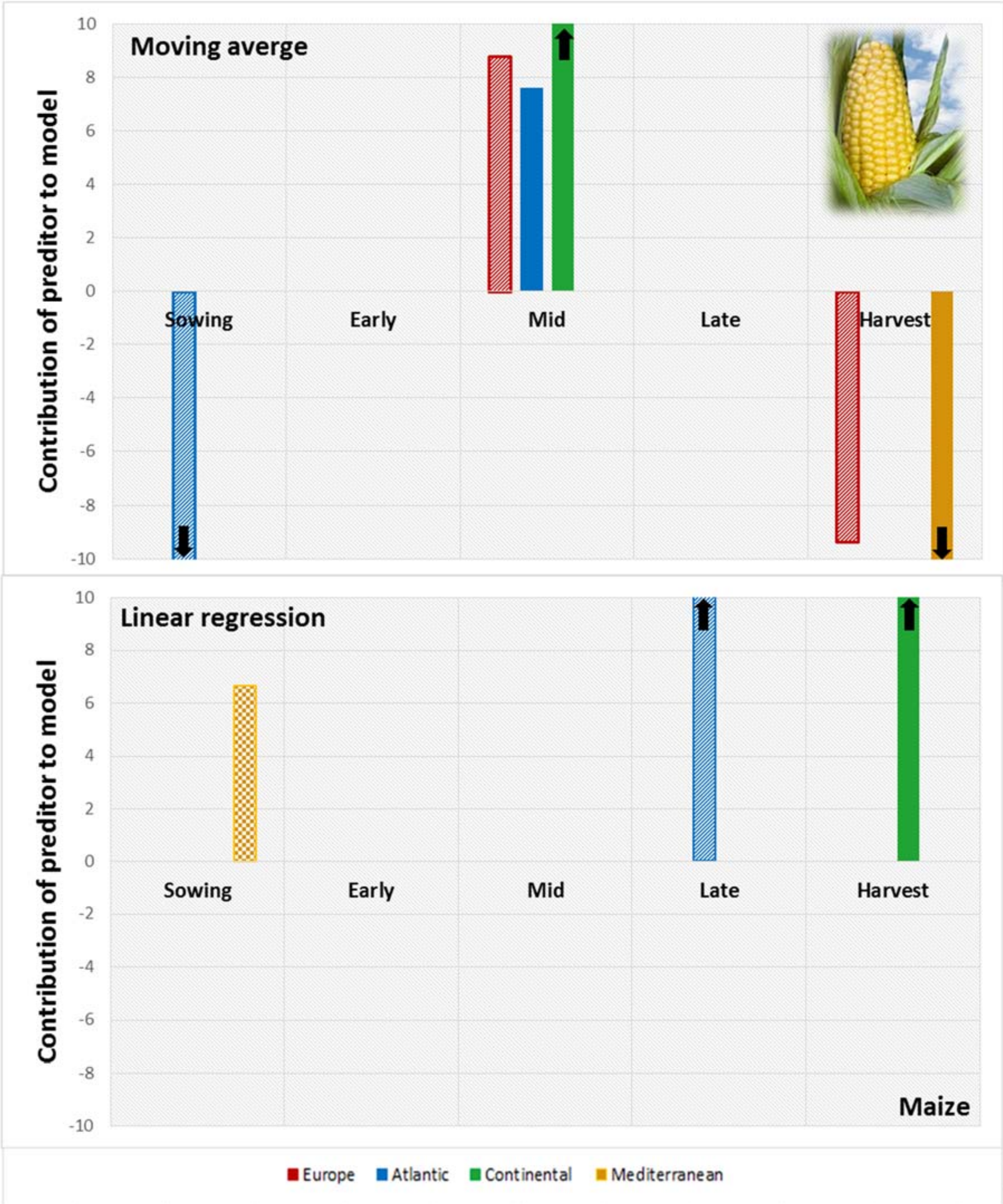

Figure 30: Contribution of predictor (slope b) to SPI models for Europe (red), Atlantic (blue), Continental (green) and Mediterranean Climate regions (yellow) divided over five parts of the growing season for maize. Here the three accumulation periods are indicated as: 1 (solid), 2 (striped) and 3 (blocked). Positive contribution refers to losses by drier than average periods (or droughts) and a negative contribution suggest crop yield losses in case of higher than normal precipitation. The arrows indicate a larger than within the range [-10 – 10] contribution. For a complete overview of the statistical model, conduct Tables 9 and 14.

4 Discussion

4.1 De-trending methods

With maize and sugar beet as an exception, according to Tables 5 – 14 and Figures 26 – 30, the moving average approach to de-trend observed crop yield data (Ano_2B_% and Ano_2B_A_%) and the alternative linear regression one (Lin_%) gave comparable results concerning sensitive parts of the growing season. Although not the exact same variables were chosen in the model (e.g. SP(E)I2_4 was replaced by 2_3 or 1_4), the contribution of each variable (positive, negative, large or small contribution) remains almost equal. However, the models based on linear regression for de-trending include in general less variables than the models using moving average and found no significant model for some (climate) regions concerning wheat, sugar beet and maize. Here, the fewer available data remaining for linear regression can play an important role.

Figure 16 illustrates the lower coefficient of determination for the linear regression method than for moving average as de-trending approaches. The linear regression values were comparable with the range found by Chen et al. (2012) when crop yields were de-trended to analyse yield change over time. Possibly a quadratic regression, suggested by Goldblum (2013), describes the 30-year data set better. In contrast to the moving average approach, linear regression performs better correlated with SPI than SPEI.

4.2 Drought indices SPI and SPEI

Both drought indices SPI and SPEI have been correlated to de-trended crop yield data, considering the hypothesis of SPEI would perform better than SPI due to the addition of evapotranspiration. However, Figure 16 shows only slight improvements from SPI to SPEI for the moving averaged de-trended data and even a decline in correlations for SPEI by the linear regression method. Figures 18 and 19 explain that SPEI only makes a small improvement over SPI during the flowering and harvesting period when foliage production is at maximum. If we consider the three major climate regions (Figures 20 and 21) it is suggested that the Continental Climate area is the only climate region were evapotranspiration plays a more important role.

The small difference between SPI and SPEI suggests that in Europe the precipitation anomalies are much more determinant for crop failure than the variations in evapotranspiration. However, the Continental Climate region has higher SPEI correlations at the end of the growing season (June and July). The summer European precipitation map (Figure 2b) illustrates that during these two months highest precipitation amounts could be expected. Probably due to enough water, the evapotranspiration plays a more important role in this part of the growing season(less serious water-limited conditions), while the two other main climate regions are experiencing lower than average rainfall.

The extra term of the PET in the SPEI contributed only to a slight improvement in crop yield correlations, concluding that the SPI already gives sufficient information. For this reason further analysis was done with SPI only using the moving average de-trending method.

4.3 Variability in crop yield correlation

4.3.1 Crops at European scale

From the results on European scale (first row Tables 5 - 14 and Figures 18 and 19) it appeared that individual crops need to be distinguished since they correlate unequally with the drought indices. Barley and wheat (both summer and winter crops, depending on the climatological and latitude regions) have a comparable trend namely: (in general) negative correlations in winter and positive links for the spring and summer period (flowering), (Figures 26 and 27).

The next two crops that have similar responses to dry/wet periods are potato and maize. On European scale (candidate months in growing season: March – September) they show that in contrast to barley and wheat the sowing and early growing season got almost no significant correlations. The correlation increases during the flowering season (June and July) and decreases drastically again during harvest (Figures 29 and 30). The one crop that does not include significant variables for the European model is sugar beet. Sugar beet seems to follow the same pattern as wheat and barley are following but has more fluctuations than the other two, making sugar beet capricious.

Elagib (2013) found in his study of sorghum and millet yield losses in Sudan that: i) the drought conditions are more important than the wet ones in predicting crop yield, and ii) crop yield losses are more likely when droughts sets in in early or mid-stages of the growing season. With the exception of wheat, the first finding applies, since the positive correlations give higher scores than the negative ones. Sugar beet also has a high value for the negative correlation in March, but is not confirmed since of a lack of significant variables in the model. The second finding disagrees with the European results for all five crops; relatively low correlations were found until the flowering season. On its turn, it agrees with Hlavinka's et al. (2009) findings of significant high sensitivity of summer droughts to crop yields in the Czech Republic.

4.3.2 Regional differences

Once we divide Europe over the three main climate regions (i.e. Atlantic, Continental and Mediterranean, Figures 22 and 23) we noticed considerable spatial differences in results for barley, wheat and potato.

Barley and wheat crop yield anomalies have the highest positive correlations in the Mediterranean area (suggesting drought sensitivity during most stages of the growing season, except harvest). On the other hand, the Atlantic area has mostly negative (suggesting wet spells are reducing crop yields in most stages of the growing season of which the sowing season is the most important, except for barley), see also Figures 26 and 27. In both cases the Continental Climate area seems to follow the trends of the Atlantic region during sowing and early growing season, but then catches up with the Mediterranean for flowering and harvest. Barley and wheat give in all regions the most significant models for the three months accumulation period (SPI3).

Potato and maize follow the same trend for the three climate regions as given on European scale, except that the Atlantic region is more extreme (in both negative and positive correlations) than the other two. What strikes most is that in contrast to wheat and barley, the statistical models for potato and maize have lower accumulation periods; one and two months (SPI1 and SPI2) are better predictors. In a study in the Czech Republic, crop yield anomalies and their correlations with SPEI (Potopová et al., 2015) this was also the case for potato, but not for maize. The accumulation period for wheat and barley was dependent on being cultivated as a winter or summer crop, in which in this study could not be distinguished due to a lack of separated crop yield data.

For sugar beet, Hlavinka's et al. (2009) found the same fluctuation pattern in the Czech Republic as we did: i.e. a strong negative relation in June and positive relation in July. For the Continental Climate region we found this sharp distinction as well, but two months forward shifted (April and May). Possible explanation is that sugar beet is a summer crop in the Czech Republic while in this study sugar beet was assumed to be a winter crop (to include the winter period of the growing season in the South European countries). As being a summer crop, the water storage of the winter period could not be used and probably makes the crop more sensitive to drought in its first months, resulting in a delayed negative correlation.

4.4 Correlation reliability

Although the statistical yield losses models all include significant variables, the correlation (R^2) between crop yield anomalies and drought indices is very low. Where Elagib (2013) found values exceeding 0.7 for crop yield anomalies correlations with SPI, this study does not exceed the 0.2 for the large areas we distinguished in our study. Potopová et al. (2015) found twice as high correlations (0.4) for the relations in the Czech Republic at country scale. For Europe and climate regions it is hard to find higher correlations, since of i) the large area includes a lot of heterogeneous data, and ii) the varying climates (still present in case of the division over climate regions). In case of Elagib (2013) the climate was much more stable and Potopová et al. (2015) worked on a smaller spatial scale. The lowest correlations were found for maize in all regions. As being the only C4 plant, maize might be me more resistant to droughts.
Furthermore, crop yield failure can also be due to phenomena that are not registered by the drought indices such as floods (usually too short temporal scale to the noticed by SP(E)I), frost, hail (in combination with winds), soil degradation, economic factors (e.g. Pielke and Downtown, 2002; Andrews et al., 1997; Morgan and Towery, 1976; Mendelsohn, 2007). Meanwhile crop yield could be ensured through irrigation. Since of all these uncertainties and low correlations this data is not advised to be used in a predictive model. However, the data could contribute as input for explanatory models.

4.5 Data limitations

The Eurostat crop yield data set includes a lot of gaps and was for some countries unusable. The data set for Germany included a lot NUTS2 regions, but most of them provided less than ten years of data. The ones that had enough data were measured every four years and therefore de-trending and relating it to droughts was impossible. Therefore only five of the tens NUTS2 regions in Germany were used.

Another drawback is the lumping of the crop yield data in the Eurostat data set, which does not make a distinction between summer of winter cultivated crops for wheat, barley and sugar beet. Potopová et al. (2015) found different relations for spring/winter sown wheat and barley, which could not be detected in our study. The same holds for irrigated (or in greenhouse-situated) crops, which, in case of relatively large areas, could drastically decrease correlations with drought indices.

The SP(E)I data set was incomplete as well, since most non-continental European regions did not have data (islands of Portugal and Spain for instance). Likewise data were not supplied for the Asian part of Turkey. Nevertheless, enough data remained for correlations in the three climate regions, but countries were incomplete.

5 Conclusions and recommendations

5.1 Conclusions

The following could be concluded in association with the research questions mentioned in the introduction:

1. The two de-trending methods for crop yields (linear regression and moving average) gave similar patterns in correlations between crop yield anomalies and drought indices SPI and SPEI. Higher correlations were obtained for the moving average method as de-trending.
2. Due to the high collinearity found between SPI and SPEI (Pearson R over 0.9 when using SPI and SPEI in the same aggregation level), the statistical models had to be treated over separate models. The correlation of the crop yield anomalies with SPEI is only a little better in the Continental Climate region, concluding that correlation with SPI can be used in Europe and that evapotranspiration data did not add much in this study.
3. The highest correlation between crop yield anomalies and SPI was reached for an accumulation period of three months (SPI3) for barley and wheat. For the other three crops SPI1 and SPI2 contributed most to the significant multiple linear regression models.
4. The coefficient of determination of the statistical models (R^2) was rather low due the large spatial scale and different climates in Europe. Due to the low values, the results can only be used in explanatory models, not in predictive ones.
5. Impacts of droughts (and wet spells) on crop yield at European scale can be observed, but regional differences in results within biogeographical regions exist due to regional climate diversity.

5.2 Recommendations

Since we assume factors other than climate to have an impact on crop yield anomalies (e.g. technological development), the Eurostat data was de-trended by the moving average (of two years) and linear regression method. It was wise to do so, since insufficient significant trends have been found including the raw (not de-trended) crop yield data set. However, these two methods can be seen as two extremes: while the linear regression method only detects one trend line for a period of 10-38 years (depending on the data availability per NUTS2 region), the moving average found a new trend every other year, which is possibly too frequent in reality. We discovered in some regions big leaps halfway the data set. In this case a break can be included, making two (linear) trend lines and more data will be included for analyses. Moreover, exponential or quadratic trend lines could be tested.

All NUTS2 regions in the crop yield data were de-trended using the moving average, where in the end only two methods remained (i: two years before and after percentage , and ii) two years before percentage). In a smaller data set the NUTS2 regions could be de-trended separately for their own best fitting de-trending period, which was beyond the European scale.

In addition to relating crop yield anomalies to only meteorological drought indices, soil moisture could be used to investigated yield losses during the growing season per crop. We did not include soil moisture values in our analysis. Oude Lenferink et al. (2014) did, using NUTS1 regions the soil moisture analysis on pan-European scale. Although relations have been found, seasonal pattern (only yearly evapotranspiration was given) and the response of crop yield to wet conditions were missing. This research suggests that crop yield prediction models should include the effect of wet spells, since the role can be very important.

As a final recommendation we would suggest to use the standardized crop yield (yield $NUTS2_n$/average yield) and then correlate them to the drought indices. Possibly, this method will give different results.

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Appendices

Appendix 1 - Codes of NUTS2 regions in study area

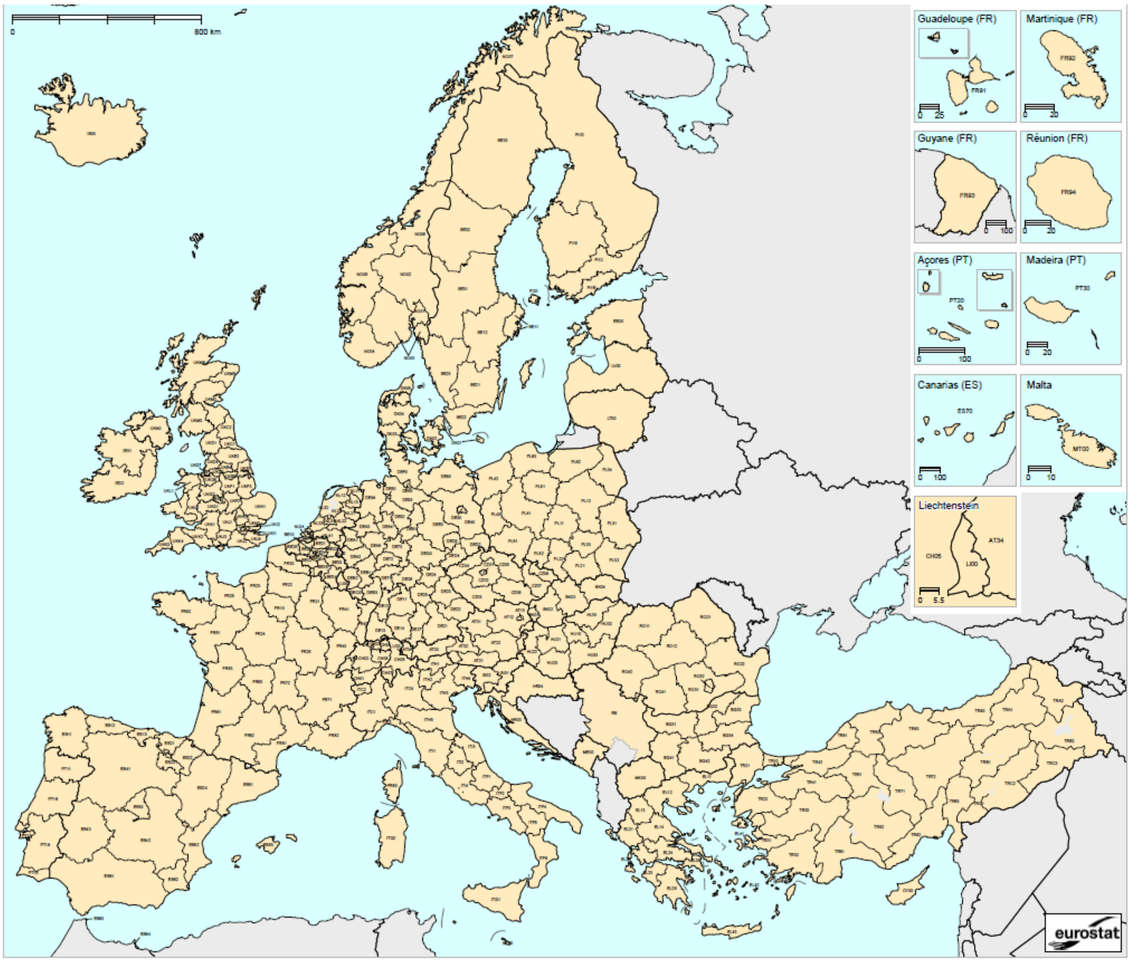

Figure A1.1: NUTS2 regions in Europe. The map shows that the sizes of all NUTS2 regions are unequal.

Table A1.1: International country codes of NUTS regions

code	country	code	country
BE	Belgium	**MT**	Malta
BG	Bulgaria	**NL**	Netherlands
CZ	Czech Republic	**AT**	Austria
DK	Denmark	**PL**	Poland
DE	Germany	**PT**	Portugal
EE	Estonia	**RO**	Romania
IE	Ireland	**SI**	Slovenia
EL	Greece	**SK**	Slovakia
ES	Spain	**FI**	Finland
FR	France	**SE**	Sweden
HR	Croatia	**UK**	United Kingdom
IT	Italy	**IS**	Iceland
CY	Cyprus	**LI**	Liechtenstein
LV	Latvia	**NO**	Norway
LT	Lithuania	**ME**	Montenegro
LU	Luxembourg	**MK**	F.Y.R. Macedonia
HU	Hungary	**TR**	Turkey

Table A1.2: Reconstruction of NUTS2 regions in Finland since 2006 (information obtained from http://www.statoids.com/ufi.html)

Full name NUTS2 region	New code	Old code
Länsi-Suomi (West Finland)	FI19	FI19
Helsinki-Uusimaa	FI1B	part of FI18
Etelä-Suomi (South Finland)	FI1C	part of FI18
Pohjois- ja Itä-Suomi (North and East Finland)	FI1D	FI13 and FI1A
Ahvenanmaa (Åland)	FI20	FI20

Appendix 2 - Statistics of Eurostat crop yield data set

Table A2.1: Statistics of the analysed crop yield data wheat AT11 – ITI4 including the number of years (N), the minimum, maximum and average crop yield production (1000 tonnes) recorded per NUTS2 region

NUTS2	N	Min.	Max.	Average	NUTS2	N	Min.	Max.	Average
BE22	35	34.5	87.0	62.1	ES24	32	297.6	820.5	473.9
BE23	35	43.1	129.6	82.1	ES30	32	24.8	101.8	64.9
BE24	19	113.2	169.4	143.4	ES41	32	829.2	2569.1	1615.5
BE25	35	71.3	295.6	199.0	ES42	32	210.0	1086.2	573.2
BE31	19	139.5	198.2	174.5	ES43	32	16.9	575.8	233.0
BE32	35	192.7	515.3	364.1	ES51	32	134.0	339.3	254.8
BE33	35	89.1	250.8	170.8	ES52	32	6.1	35.3	21.7
BE34	35	8.3	40.2	27.6	ES53	32	5.1	19.4	11.0
BE35	35	97.0	303.2	211.6	ES61	32	329.9	2266.4	1344.3
CZ01	12	15.6	37.3	25.4	ES62	32	1.9	41.8	16.6
CZ02	12	604.3	1064.2	831.0	FR10	33	1010.0	2272.5	1796.8
CZ03	12	439.4	871.3	687.5	FR21	33	1350.7	3608.5	2806.5
CZ04	12	201.4	482.8	320.0	FR22	33	1771.0	4734.2	3545.0
CZ05	12	402.4	677.7	554.4	FR23	33	693.4	2198.1	1569.2
CZ06	12	548.2	1098.5	897.2	FR24	33	2589.7	6461.8	4946.2
CZ07	12	227.2	550.4	477.8	FR25	33	330.6	1589.7	1027.8
CZ08	12	129.9	234.3	193.7	FR26	33	887.8	2574.9	1847.3
DE80	15	921.6	2671.2	1762.6	FR30	33	955.1	2693.1	1847.1
DEC0	30	27.3	61.7	40.1	FR41	33	267.9	1702.8	1085.9
DEF0	30	636.8	1910.7	1266.3	FR42	33	187.7	420.4	302.5
DEG0	15	866.7	1760.1	1253.8	FR43	33	89.0	494.0	278.5
EE00	15	57.1	196.6	109.6	FR51	33	873.9	2863.4	1820.6
IE01	20	73.0	154.8	104.0	FR52	33	483.2	2201.9	1403.6
IE02	20	465.7	864.2	624.7	FR53	33	883.4	2941.5	1885.7
EL11	19	267.4	566.0	392.9	FR61	33	258.5	595.2	433.8
EL12	19	444.0	1060.8	681.2	FR62	33	740.8	1931.8	1385.4
EL13	19	197.6	374.0	298.8	FR63	33	82.8	138.9	110.0
EL14	24	291.0	770.2	483.6	FR71	33	452.7	927.5	646.5
EL23	19	35.7	65.1	48.8	FR72	33	297.6	741.2	531.3
EL24	19	232.0	380.0	281.2	FR81	33	24.7	376.9	237.7
EL25	19	29.4	49.1	40.8	FR82	33	22.3	294.2	207.1
EL30	19	5.4	19.5	13.6	ITC1	32	353.1	705.0	553.2
EL41	19	3.7	9.5	7.2	ITC4	32	204.8	865.0	455.4
EL42	19	4.3	10.4	8.0	ITH3	32	206.1	681.5	384.6
ES11	32	45.8	76.5	60.1	ITH4	32	16.8	84.5	38.5
ES21	32	40.2	162.0	96.8	ITI1	32	343.2	899.6	601.2
ES22	32	115.0	358.7	232.8	ITI2	32	182.4	522.5	402.6
ES23	32	31.8	200.6	113.3	ITI4	32	200.2	670.3	450.2

Table A2.2: Statistics of the analysed crop yield data wheat ITF1 – UKN0 including the number of years (N), the minimum, maximum and average crop yield production (1000 tonnes) recorded per NUTS2 region

NUTS2	N	Min.	Max.	Average	NUTS2	N	Min.	Max.	Average
ITF1	32	174.9	334.8	271.0	PL22	15	174.9	288.7	236.3
ITF2	32	133.1	281.4	211.4	PL31	15	688.8	1135.2	951.6
ITF3	32	201.7	402.6	329.3	PL32	15	333.1	454.3	399.2
ITF4	32	508.0	1284.6	904.0	PL33	15	161.8	305.8	254.9
ITF5	32	187.1	596.1	377.9	PL34	15	97.3	248.0	160.0
ITF6	32	92.3	263.3	188.6	PL41	15	644.6	1053.9	885.5
ITG1	32	407.5	1177.4	811.5	PL42	15	532.2	933.5	739.4
ITG2	32	43.7	220.6	128.4	PL43	15	106.7	280.7	196.3
LV00	17	190.2	676.5	400.4	PL51	15	910.4	1376.1	1159.1
LT00	19	549.4	1722.5	1072.8	PL52	15	557.8	934.9	730.8
LU00	32	15.7	80.0	44.8	PL61	15	605.0	888.1	766.4
HU10	15	111.8	340.9	248.2	PL62	15	464.2	698.3	569.2
HU21	15	366.9	703.1	569.0	PL63	15	528.5	688.9	594.9
HU22	15	298.8	632.5	485.7	PT11	24	5.9	51.4	23.9
HU23	15	431.7	957.0	699.3	PT16	11	4.5	15.3	8.7
HU31	15	215.0	658.7	502.5	PT18	11	64.9	371.0	195.7
HU32	15	415.9	1247.1	844.6	RO11	15	179.9	790.4	457.5
HU33	15	681.7	1607.7	1088.4	RO12	15	241.5	537.8	347.5
NL11	35	129.9	313.0	217.2	RO21	15	131.0	885.0	471.2
NL12	35	17.1	64.7	33.1	RO22	15	127.2	1792.4	1008.6
NL13	35	8.4	42.1	25.5	RO31	15	315.0	2412.9	1474.1
NL21	30	1.3	19.0	7.3	RO32	15	17.8	100.8	56.4
NL22	30	15.7	118.1	42.1	RO41	15	223.5	1629.6	965.5
NL23	30	67.8	158.7	122.4	RO42	15	448.2	1214.1	751.7
NL32	35	44.5	98.3	75.4	SK0S	14	930.0	1938.0	1564.0
NL33	35	55.7	152.8	117.1	SK01	13	51.0	92.0	74.6
NL34	35	85.8	318.6	229.2	SK02	15	642.0	1229.0	1012.1
NL41	35	27.0	130.8	86.3	SK03	15	97.0	278.0	198.1
NL42	35	27.0	68.7	49.5	SK04	15	140.0	431.0	292.0
AT11	35	108.6	236.3	170.3	FI19	15	3.2	196.7	87.3
AT12	35	457.8	1110.4	811.6	SE11	17	43.9	96.2	70.8
AT13	35	5.7	13.8	8.8	SE12	17	446.5	932.1	726.5
AT21	35	7.4	16.0	11.5	SE21	11	88.9	131.7	114.2
AT22	35	24.9	54.4	41.0	SE22	17	394.1	860.1	670.0
AT31	35	209.2	340.4	287.1	SE23	11	274.6	532.5	430.9
PL11	15	243.3	399.2	320.5	SE31	17	12.6	36.1	24.7
PL12	15	414.1	580.1	483.0	UKH1	21	969.4	2840.0	2108.0
PL21	15	257.0	397.4	358.1	UKN0	29	2.0	65.1	29.1

Table A2.3: Statistics of the analysed crop yield data barley AT11 – ITG1 including the number of years (N), the minimum, maximum and average crop yield production (1000 tonnes) recorded per NUTS2 region

NUTS2	N	Min.	Max.	Average	NUTS2	N	Min.	Max.	Average
BE22	39	18.0	53.5	30.9	ES43	36	7.1	140164.0	10550.7
BE23	39	12.8	89.6	38.6	ES51	36	190.1	824678.0	72939.4
BE24	23	36.3	60.0	43.6	ES52	36	14.5	46398.0	4030.2
BE25	39	8.1	116.0	44.4	ES53	36	8.0	55859.0	5662.8
BE31	23	23.5	55.7	37.9	ES61	36	50.2	265326.0	24051.5
BE32	39	41.2	167.5	92.3	ES62	36	7.9	36309.0	2931.3
BE33	39	37.9	127.6	74.6	FR10	37	265.2	5062095.0	482776.1
BE34	39	9.0	42.4	20.8	FR21	37	957.7	17744702.0	1798879.1
BE35	39	49.8	130.8	95.4	FR22	37	573.5	7873585.0	450828.7
BG41	13	7.4	10746.0	846.0	FR23	37	241.3	4242028.0	292131.5
CZ01	16	6.7	910072.0	58219.0	FR24	37	872.0	14814219.0	401658.0
CZ02	16	283.5	32402005.0	2067865.5	FR25	37	133.7	2666303.0	72282.0
CZ03	16	272.0	28449214.0	1814598.8	FR26	37	672.4	1255.3	970.9
CZ04	16	108.5	1208224.0	91066.0	FR30	37	437.0	4589702.0	254112.4
CZ05	16	197.7	20061103.0	1279215.0	FR41	37	499.8	877885.0	24506.5
CZ06	16	377.6	36217899.0	2315631.2	FR42	37	24.6	32895.0	2471.2
CZ07	16	206.2	23590634.0	1504605.4	FR43	37	101.1	1952903.0	66566.6
CZ08	16	75.5	7933519.0	500807.4	FR51	37	162.2	3080375.0	177851.8
DE80	15	693.1	1159.9	948.3	FR52	37	377.7	5211145.0	515684.1
DEC0	30	31.7	55.2	42.1	FR53	37	370.1	584865.0	36019.9
DEF0	30	323.3	939.8	640.6	FR61	37	84.5	957025.0	81688.8
DEG0	15	637.7	954.6	769.4	FR62	37	338.6	4068555.0	137966.4
EE00	19	186.4	622.7	339.6	FR63	37	47.9	58498.0	4712.8
IE01	24	204.9	294053.0	34896.7	FR71	37	175.7	2355591.0	79141.8
IE02	24	696.0	974785.0	81835.2	FR72	37	116.8	1442376.0	48961.4
EL11	23	24.3	86.8	47.0	FR81	37	20.1	52272.0	4597.1
EL12	23	25.8	246.3	85.6	FR82	37	25.7	372833.0	20137.8
EL13	23	46.0	131.3	87.5	ITC1	35	12.0	110761.0	5482.4
EL14	28	40.7	213.8	101.3	ITC4	35	67.2	126606.0	8930.9
EL23	23	2.5	19.9	15.0	ITH3	35	36.9	46404.0	3797.6
EL24	23	17.5	94.4	40.4	ITH4	35	18.2	40873.0	2210.4
EL25	23	6.2	21.3	12.6	ITI1	35	25.8	47856.0	2520.6
EL41	23	.2	20.0	13.8	ITI2	35	12.1	97496.0	8031.8
EL42	23	4.9	21.9	10.6	ITI4	35	27.8	48279.0	1438.3
ES11	36	0.0	1014.0	30.7	ITF1	35	9.7	75824.0	6259.2
ES21	36	39.1	78568.0	6163.9	ITF2	35	3.6	27.1	18.6
ES22	36	212.3	362768.0	27713.9	ITF3	35	7.2	51704.0	2697.2
ES23	36	55.1	97975.0	7545.1	ITF4	35	32.0	83963.0	4698.2
ES24	36	523.4	1731535.0	140878.0	ITF5	35	25.2	67765.0	3830.9
ES30	36	44.5	134695.0	9463.3	ITF6	35	9.5	23718.0	1891.7
ES41	36	1485.0	3497332.0	332882.5	ITG1	35	11.5	31372.0	2233.5
ES42	36	630,0	2383107,0	167123,6					

Table A2.4: Statistics of the analysed crop yield data barley ITG2 – TR81 including the number of years (N), the minimum, maximum and average crop yield production (1000 tonnes) recorded per NUTS2 region

NUTS2	N	Min.	Max.	Average	NUTS2	N	Min.	Max.	Average
ITG2	35	21.6	24073.0	1900.4	PL61	19	285.5	590.6	412.2
LV00	21	228.4	764.9	347.9	PL62	19	123.2	235.6	165.4
LT00	23	550.0	1699.2	953.8	PL63	19	145.4	213.5	173.5
LU00	36	32.8	43003.0	4551.6	PT16	15	.5	3828.0	256.5
HU10	19	28.2	62723.0	11535.7	PT17	15	.2	1788.0	197.7
HU21	19	83.5	123107.0	23898.7	PT18	15	9.5	66645.0	8930.2
HU22	19	155.5	204214.0	39294.2	RO11	19	29.6	112949.0	18438.2
HU23	19	130.1	189114.0	35474.8	RO12	19	30.9	94111.0	17252.5
HU31	19	86.1	113745.0	20207.2	RO21	19	24.6	66216.0	9838.1
HU32	19	78.4	148692.0	25850.8	RO22	19	48.8	536965.0	94055.8
HU33	19	151.4	297705.0	54626.0	RO31	19	59.0	500292.0	63069.4
NL11	39	44.1	47282.0	1272.0	RO32	19	2.6	26058.0	3640.9
NL12	39	2.8	6788.0	184.6	RO41	19	18.1	106256.0	13996.9
NL13	39	7.4	55238.0	1458.6	RO42	19	77.0	192439.0	25102.1
NL21	34	1.6	10361.0	315.0	SK01	19	0.0	184465.0	9733.2
NL22	34	6.4	12719.0	388.4	SK02	19	258.0	3419783.0	180427.2
NL23	34	7.4	10377.0	323.5	SK03	19	24.0	246509.0	13039.6
NL32	39	4.8	7192.0	194.6	SK04	19	36.3	609735.0	32213.7
NL33	39	3.0	5391.0	153.3	FI19	19	479.1	916.1	733.9
NL34	39	17.0	18215.0	502.4	SE11	12	24.2	63.3	40.4
NL41	39	8.0	7181.0	201.4	SE12	21	317.5	674.0	479.9
NL42	39	11.7	23442.0	624.0	SE21	15	96.8	220.9	162.9
AT11	39	49.4	45524.0	4063.7	SE22	21	314.3	592.6	502.1
AT12	39	416.5	471051.0	30425.6	SE23	15	202.5	424.3	288.9
AT13	39	.9	1747.0	103.9	SE31	18	75.6	176.5	115.8
AT21	39	22.0	30058.0	2981.3	SE32	21	8.9	30.2	17.8
AT22	39	39.8	44823.0	2359.1	SE33	21	18.5	47.7	34.6
AT31	39	132.5	272102.0	25762.3	UKH1	21	740.0	1273.3	1044.9
AT32	39	1.9	2647.0	186.3	UKN0	29	111.7	222.0	176.5
PL11	19	89.1	253.1	147.7	TR10	12	18	45	34.1
PL12	19	135.7	237.5	185.0	TR21	12	143	222	180.7
PL21	19	114.7	179.1	142.0	TR22	12	102	145	129.7
PL22	19	90.3	132.1	113.7	TR31	12	23	52	29.8
PL31	19	295.3	544.4	384.6	TR32	12	172	271	210.8
PL32	19	52.4	93.0	72.9	TR33	12	689	976	817.8
PL33	19	125.7	210.5	160.5	TR41	12	277	458	347.9
PL34	19	39.0	91.6	66.1	TR42	12	68	90	79.3
PL41	19	399.7	905.6	587.5	TR51	12	509	935	686.3
PL42	19	176.7	357.9	268.3	TR52	12	715	1719	1198.5
PL43	19	51.2	132.4	98.5	TR61	12	235	380	299.6
PL51	19	211.3	360.3	278.4	TR81	12	14	30	23.4

PL52	19	213.9	331.0	265.7					

Table A2.5: Statistics of the analysed crop yield data potato AT11 – HU22 including the number of years (N), the minimum, maximum and average crop yield production (1000 tonnes) recorded per NUTS2 region

NUTS2	N	Min	Max	Average	NUTS2	N	Min	Max	Average
AT11	39	7.2	83.8	27.4	**EL41**	22	4.4	14.5	10.7
AT12	39	433.0	975.5	637.0	**EL42**	22	18.1	45.6	34.1
AT13	39	0.5	4.0	1.9	**EL43**	30	70.3	103.5	88.0
AT21	39	6.1	120.1	36.4	**ES11**	36	411.4	1703.0	993.3
AT22	39	13.9	165.4	51.8	**ES12**	36	20.6	194.7	93.3
AT31	39	35.8	302.8	108.2	**ES13**	36	1.2	55.2	32.1
AT32	39	2.4	20.0	7.9	**ES21**	36	42.3	274.7	145.5
AT33	39	10.1	68.9	28.6	**ES22**	36	13.1	128.3	57.0
AT34	39	0.6	7.4	2.0	**ES23**	36	71.3	330.0	196.9
BE10	36	0.2	7.8	1.3	**ES24**	36	6.4	231.7	116.9
BE21	39	25.2	194.0	78.2	**ES30**	36	2.0	85.7	53.5
BE22	39	15.6	145.0	62.6	**ES41**	36	670.4	1473.0	992.7
BE23	39	142.1	588.0	363.0	**ES42**	36	81.9	404.9	218.2
BE24	23	0.0	340.0	212.9	**ES43**	36	26.1	179.7	85.0
BE25	39	1.1	1080.7	731.3	**ES51**	36	27.9	359.1	194.6
BE31	23	0.0	312.0	139.9	**ES52**	36	33.8	283.2	153.6
BE32	39	1.0	924.8	481.7	**ES53**	36	27.0	97.4	72.6
BE33	39	9.2	201.8	52.2	**ES61**	36	96.8	696.6	540.3
BE34	39	7.6	36.6	16.8	**ES62**	36	15.4	107.9	69.2
BE35	39	9.0	192.0	70.8	**FI19**	16	382.1	531.9	464.0
BG41	10	101.0	179.9	143.6	**FI20**	16	15.8	23.6	20.2
CZ01	12	0.3	21.1	7.4	**FR10**	37	78.6	300.9	149.4
CZ02	12	133.6	296.9	201.8	**FR21**	37	167.8	1036.1	580.7
CZ03	12	112.2	324.3	210.5	**FR22**	37	697.8	2241.4	1756.7
CZ04	12	17.5	79.0	47.3	**FR23**	37	71.6	595.6	295.4
CZ05	12	70.9	185.9	113.0	**FR24**	37	77.6	595.3	250.8
CZ06	12	259.1	622.9	440.9	**FR25**	37	45.5	125.1	69.8
CZ07	12	25.2	158.2	82.6	**FR26**	37	13.7	127.2	46.1
CZ08	12	19.5	112.0	58.2	**FR30**	37	746.7	2463.3	1758.8
DE30	11	0.2	1.0	0.5	**FR41**	37	7.2	105.8	28.5
DE50	11	0.0	0.9	0.5	**FR42**	37	30.9	181.8	66.6
DE60	23	0.5	1.7	0.9	**FR43**	37	2.0	43.6	14.5
DE80	15	378.5	1572.8	654.1	**FR51**	37	27.3	320.6	98.7
DEC0	30	4.4	178.8	28.5	**FR52**	37	263.6	1076.3	542.4
DEF0	30	93.5	251.6	167.6	**FR53**	37	11.6	224.4	50.0
DEG0	15	75.3	741.7	204.5	**FR61**	37	47.7	256.3	118.3
EE00	20	92.6	669.1	363.7	**FR62**	37	8.4	301.2	91.4
EL11	22	55.4	201.3	122.9	**FR63**	37	5.2	181.8	52.0
EL12	22	20.4	69.0	54.8	**FR71**	37	46.2	380.7	156.4

EL13	22	33.6	61.4	44.6	FR72	37	12.0	248.1	69.8
EL14	28	3.4	65.4	31.4	FR81	37	20.1	109.7	60.7
EL21	22	30.7	51.2	40.5	FR82	37	22.9	217.5	89.8
EL22	22	17.0	23.1	20.0	FR83	37	0.4	9.0	3.4
EL23	22	139.5	294.9	241.2	HU10	17	82.7	228.0	129.3
EL24	22	41.3	125.4	93.4	HU21	17	25.1	93.3	49.0
EL25	22	85.4	189.0	130.9	HU22	17	43.8	183.6	107.2
EL30	22	4.1	10.5	6.2					

Table A2.6: Statistics of the analysed crop yield data potato HU23 – UKN0 including the number of years (N), the minimum, maximum and average crop yield production (1000 tonnes) recorded per NUTS2 region

NUTS2	N	Min	Max	Average	NUTS2	N	Min	Max	Average
HU23	17	20.6	127.7	65.3	PL34	15	355.7	2016.4	1097.5
HU31	17	29.5	210.4	91.3	PL41	15	761.0	2414.4	1586.9
HU32	17	64.0	301.6	163.2	PL42	15	414.4	778.4	594.6
HU33	17	130.8	294.8	209.4	PL43	15	131.0	319.8	256.0
IE01	24	59.0	216.0	145.4	PL51	15	440.7	1282.6	818.7
IE02	24	172.8	520.3	343.1	PL52	15	216.1	637.3	398.0
ITC1	35	24.2	223.9	116.5	PL61	15	431.1	1268.2	788.1
ITC2	35	0.0	10.0	6.6	PL62	15	204.9	804.0	478.9
ITC3	35	0.0	66.5	31.8	PL63	15	542.6	961.0	733.8
ITC4	35	0.0	152.2	78.2	PT11	28	123.4	590.3	319.1
ITF1	35	125.5	350.9	208.5	PT15	28	4.5	20.8	13.7
ITF2	35	12.6	60.5	24.1	PT16	15	130.2	469.4	265.3
ITF3	35	241.8	940.6	503.4	PT17	15	22.4	92.6	49.4
ITF4	35	57.9	243.5	158.9	PT18	15	36.1	67.0	51.3
ITF5	33	0.0	38.6	13.8	RO11	15	603.9	923.6	796.5
ITF6	35	65.4	184.9	154.8	RO12	15	827.9	1326.7	1028.4
ITG1	35	90.0	270.3	165.6	RO21	15	680.3	994.3	889.5
ITG2	35	3.8	64.8	40.2	RO22	15	95.7	196.4	129.7
ITH3	35	99.9	357.3	185.7	RO31	15	204.9	348.0	281.2
ITH4	35	11.6	96.8	32.5	RO32	15	6.1	16.2	12.6
ITI1	35	36.8	139.0	83.9	RO41	15	90.8	276.8	182.2
ITI2	35	5.9	39.5	19.0	RO42	15	323.7	483.8	409.0
ITI4	35	53.2	196.2	132.5	SE12	21	73.0	147.2	93.8
LT00	23	420.6	2044.3	1189.8	SE21	15	67.2	106.8	80.2
LU00	37	16.4	55.0	25.1	SE22	21	294.1	702.3	494.6
LV00	21	236.8	1271.7	740.4	SE23	12	145.3	226.7	175.4
MT00	22	9.5	34.4	24.0	SE31	21	31.6	63.4	41.9
NL11	39	839.8	1255.9	1075.1	SE32	21	3.9	16.4	7.6
NL12	39	157.1	343.6	279.1	SE33	21	12.3	34.9	20.1
NL13	39	1049.2	1618.6	1313.5	SK01	19	0.0	43.2	22.6
NL21	34	203.5	406.0	299.9	SK02	19	44.0	204.0	96.0
NL22	34	92.9	297.0	200.4	SK03	19	22.0	299.0	106.1
NL23	34	647.2	1167.5	991.6	SK04	19	32.0	274.0	117.6
NL31	39	3.0	17.3	7.1	TR10	10	0.1	3.2	1.0

NL32	39	274.7	531.3	438.2	**TR21**	12	13.0	36.2	28.0
NL33	39	268.6	641.0	521.8	**TR22**	12	10.0	40.3	27.2
NL34	39	382.8	996.9	757.6	**TR31**	12	225.6	591.0	364.0
NL41	39	297.2	1025.5	661.6	**TR32**	12	18.0	105.5	71.2
NL42	39	132.1	446.8	321.9	**TR33**	12	244.9	484.0	361.3
PL11	15	866.0	3386.8	1956.8	**TR41**	12	81.9	134.0	100.8
PL12	15	1262.8	4889.5	2781.3	**TR42**	12	281.0	372.1	340.2
PL21	15	647.7	1678.7	1147.4	**TR51**	12	3.0	47.4	31.4
PL22	15	273.0	1016.6	608.1	**TR52**	12	123.7	485.0	206.4
PL31	15	734.7	3104.4	1720.2	**TR61**	12	49.0	82.9	67.4
PL32	15	790.3	1767.4	1253.6	**TR81**	12	8.0	23.5	18.3
PL33	15	430.9	1318.5	863.9	**UKN0**	24	250.8	466.0	324.0

Table A2.7: Statistics of the analysed crop yield data sugar beet AT11 – ITF1 including the number of years (N), the minimum, maximum and average crop yield production (1000 tonnes) recorded per NUTS2 region

NUTS2	N	Min	Max	Average	NUTS2	N	Min	Max	Average
AT11	39	163.3	355.5	276.3	**ES24**	36	0.0	288.0	65.9
AT12	39	1167.8	2751.1	2047.3	**ES30**	36	0.0	14.9	3.1
AT13	39	15.9	35.2	22.5	**ES41**	36	1843.9	5308.0	4061.5
AT22	39	8.8	18.6	14.3	**ES42**	36	0.0	1069.1	503.8
AT31	39	210.8	495.0	383.3	**ES43**	36	0.0	240.0	95.3
BE10	36	0.1	15.1	2.9	**ES61**	36	383.8	3593.2	2137.7
BE21	39	16.7	53.6	36.9	**ES62**	35	0.0	34.7	3.4
BE22	39	319.3	507.1	394.6	**FI19**	19	158.6	370.0	254.3
BE23	39	219.2	445.6	338.4	**FI20**	19	0.0	52.7	27.4
BE24	23	366.9	602.0	485.5	**FR10**	37	2010.8	3989.5	2990.7
BE25	39	513.9	1052.4	795.4	**FR21**	37	4969.2	9779.5	6655.8
BE31	23	603.5	938.3	728.1	**FR22**	37	8156.9	12598.9	10781.3
BE32	39	1.4	2039.1	1509.7	**FR23**	37	1313.9	2107.6	1696.0
BE33	39	601.3	937.8	756.4	**FR24**	37	1179.8	2957.4	1939.6
BE34	39	1.1	13.6	8.5	**FR25**	37	423.7	890.9	539.9
BE35	39	549.2	874.6	670.7	**FR26**	37	104.4	605.3	420.6
CZ01	16	11.4	32.1	20.7	**FR30**	37	3365.4	5508.3	4356.6
CZ02	16	691.8	1152.8	953.4	**FR41**	37	1.6	35.1	18.7
CZ04	16	136.1	360.7	210.4	**FR42**	37	185.0	668.5	355.7
CZ05	16	618.3	1003.7	794.0	**FR43**	37	0.0	93.1	58.1
CZ06	16	251.4	547.2	364.2	**FR51**	37	19.4	75.8	40.3
CZ07	16	535.3	1084.9	809.9	**FR52**	37	0.0	16.3	1.3
CZ08	16	247.9	458.1	326.4	**FR61**	37	0.0	170.6	9.8
DE80	15	1029.4	1847.2	1444.9	**FR71**	37	0.0	23.1	12.5
DEF0	30	493.6	972.3	754.0	**FR72**	37	110.5	430.7	248.7
DEG0	15	537.3	796.1	631.6	**HU10**	19	17.0	153.1	76.9
EE00	16	0.0	12.7	2.5	**HU21**	19	127.3	428.1	245.9
EL11	23	101.6	1328.0	750.8	**HU22**	19	101.8	892.8	459.0
EL12	23	155.2	1292.5	789.0	**HU23**	19	106.3	540.3	297.6
EL13	23	33.4	235.2	143.0	**HU31**	19	4.0	218.8	104.9

EL14	28	24.2	794.3	436.8	**HU32**	19	42.3	1427.7	720.0
EL24	23	6.5	172.8	80.0	**HU33**	19	91.6	1178.8	404.8
ES21	36	62.6	241.4	156.3	**ITC1**	32	0.0	741.0	371.4
ES22	36	0.3	167.1	25.0	**ITC4**	32	488.5	2129.5	1147.4
ES23	36	99.8	245.8	169.3	**ITF1**	32	65.6	571.2	280.5

Table A2.8: Statistics of the analysed crop yield data sugar beet ITF2 – TR61 including the number of years (N), the minimum, maximum and average crop yield production (1000 tonnes) recorded per NUTS2 region

NUTS2	N	Min	Max	Average	NUTS2	N	Min	Max	Average
ITF2	32	27.7	310.0	130.3	**PL43**	19	50.6	434.5	151.0
ITF3	32	3.6	202.1	66.8	**PL51**	19	919.4	1877.8	1267.3
ITF4	32	400.4	1284.3	752.6	**PL52**	19	646.6	1547.9	997.5
ITF5	32	18.0	298.4	134.8	**PL61**	19	1611.2	2726.3	2159.3
ITF6	32	0.0	265.6	120.6	**PL62**	19	140.8	282.8	204.0
ITG2	32	0.0	287.5	160.5	**PL63**	19	402.8	732.5	565.7
ITH3	32	894.7	3161.1	2052.2	**PT16**	14	0.0	42.4	17.2
ITH4	32	24.7	476.7	221.6	**PT17**	14	0.0	75.9	27.4
ITI1	32	0.0	491.0	302.0	**PT18**	14	0.0	534.7	255.3
ITI2	32	0.0	316.1	142.6	**RO11**	19	121.6	602.1	264.6
ITI4	32	15.3	403.5	242.6	**RO12**	19	129.4	564.0	315.6
LT00	23	339.1	1052.4	821.4	**RO21**	19	148.7	864.5	366.4
LV00	17	228.2	622.3	429.6	**RO22**	17	1.4	308.3	90.1
NL11	38	550.6	1140.0	803.6	**RO31**	18	0.0	360.1	68.5
NL12	38	185.0	359.6	246.7	**RO41**	15	0.0	102.7	24.7
NL13	38	468.6	998.2	751.0	**RO42**	19	6.1	393.8	116.3
NL21	33	77.2	153.2	121.5	**SE21**	15	8.5	303.6	141.6
NL22	33	162.7	329.8	237.4	**SE22**	21	1853.4	2463.2	2187.8
NL23	33	767.7	1317.1	988.4	**SE23**	15	27.3	55.5	38.8
NL31	38	3.4	234.9	14.7	**SK01**	19	0.0	93.7	51.7
NL32	38	10.8	632.6	452.6	**SK02**	19	633.6	1582.3	1087.9
NL33	38	356.8	666.5	488.8	**SK03**	19	2.1	109.0	37.6
NL34	38	451.2	1213.1	948.2	**SK04**	17	0.0	192.0	57.6
NL41	38	580.1	1005.3	765.2	**TR10**	11	1.0	3.1	1.9
NL42	38	448.2	852.3	648.3	**TR21**	12	63.0	313.4	199.1
PL11	19	280.6	749.3	436.7	**TR22**	12	16.0	170.5	87.4
PL12	19	504.2	1269.0	864.2	**TR31**	10	0.6	5.6	3.2
PL21	19	44.4	128.3	78.0	**TR32**	12	150.0	345.1	221.3
PL22	19	76.3	193.5	123.9	**TR33**	12	681.3	1560.8	1070.2
PL31	19	1362.7	2886.2	1913.9	**TR41**	12	1018.5	2081.2	1363.7
PL32	19	160.5	388.9	259.5	**TR42**	12	55.0	426.1	266.1
PL33	19	170.2	649.6	377.1	**TR51**	12	274.5	838.9	554.1
PL34	19	0.0	246.1	151.1	**TR52**	12	2323.8	5239.4	3669.0
PL41	19	1734.2	2908.3	2382.8	**TR61**	12	339.2	630.7	433.5

Table A2.9: Statistics of the analysed crop yield data maize AT11 – FR83 including the number of years (N), the minimum, maximum and average crop yield production (1000 tonnes) recorded per NUTS2 region

NUTS2	N	Min	Max	Average	NUTS2	N	Min	Max	Average
AT11	35	60.0	254.3	164.1	ES13	32	0.1	15.6	4.6
AT12	35	203.6	649.1	416.6	ES21	32	1.3	9.8	4.4
AT13	35	0.4	4.5	1.8	ES22	32	64.2	195.4	121.1
AT21	35	77.3	207.0	128.9	ES23	32	4.8	26.4	12.6
AT22	35	351.9	772.1	539.6	ES24	32	240.7	923.9	518.4
AT31	35	226.6	563.1	358.7	ES30	32	25.1	134.2	72.1
BE21	36	1.6	108.8	36.1	ES41	32	27.6	1291.4	486.3
BE22	36	1.7	104.8	29.7	ES42	32	66.8	768.8	457.7
BE23	36	4.4	223.4	73.3	ES43	32	14.0	771.0	456.1
BE24	20	7.3	142.2	71.1	ES51	32	153.5	429.8	271.1
BE25	36	7.7	214.0	63.4	ES52	32	3.4	101.2	33.9
BE31	20	1.8	20.9	5.9	ES53	32	0.0	9.3	2.7
BE32	36	1.3	33.3	9.5	ES61	32	49.9	643.4	354.4
BE33	36	0.7	6.5	2.6	ES62	32	1.7	18.0	9.3
BE35	36	0.1	13.5	3.8	FR10	33	248.7	898.1	493.1
BG41	10	15.1	51.0	35.9	FR21	33	267.6	762.8	457.0
CZ02	12	38.5	132.7	74.3	FR22	33	137.4	612.2	367.4
CZ03	12	0.5	63.5	25.1	FR23	33	26.8	153.5	81.9
CZ04	12	1.9	34.6	11.4	FR24	33	836.6	1763.7	1289.6
CZ05	12	10.9	125.3	51.1	FR25	33	8.7	183.0	111.4
CZ06	12	44.4	378.7	171.8	FR26	33	182.3	506.9	387.1
CZ07	12	15.1	143.0	74.6	FR30	33	6.9	131.1	48.9
CZ08	12	1.4	39.9	18.7	FR41	33	6.3	143.5	76.8
DE80	15	0.1	48.8	20.3	FR42	33	117.5	1469.2	841.8
DEF0	26	0.0	4.8	1.8	FR43	33	27.9	318.9	157.6
DEG0	15	0.2	54.1	32.7	FR51	33	65.7	1358.3	833.1
EL11	18	449.9	897.6	670.0	FR52	33	19.7	1228.7	629.9
EL12	18	401.2	667.5	500.2	FR53	33	191.0	1945.1	1163.0
EL13	18	20.0	201.2	110.4	FR61	33	1428.2	3556.8	2734.3
EL14	23	79.9	315.4	202.8	FR62	33	836.4	2078.9	1549.8
EL21	18	130.9	254.4	159.0	FR63	33	20.6	72.4	43.0
EL22	18	1.6	2.2	1.9	FR71	33	412.1	1343.2	932.2
EL23	18	284.4	366.2	330.3	FR72	33	105.9	355.2	223.1
EL24	18	63.4	124.0	82.8	FR81	33	16.0	55.4	36.1
EL25	18	21.8	35.3	30.3	FR82	33	28.8	99.7	66.6
ES11	32	96.2	485.3	291.4	FR83	33	3.4	9.0	6.2

Table A2.10: Statistics of the analysed crop yield data maize HU21 – TR61 including the number of years (N), the minimum, maximum and average crop yield production (1000 tonnes) recorded per NUTS2 region

NUTS2	N	Min	Max	Average	NUTS2	N	Min	Max	Average
HU21	15	424.5	1210.2	797.5	PL34	15	1.0	34.5	13.2
HU22	15	454.2	917.0	649.3	PL41	15	38.2	331.9	186.3
HU23	15	1052.2	2572.0	1888.8	PL42	15	0.9	49.1	20.2
HU31	15	161.5	382.9	254.7	PL43	15	5.5	120.4	55.2
HU32	15	803.2	2099.3	1379.8	PL51	15	80.9	618.6	328.3
HU33	15	759.5	1883.9	1442.8	PL52	15	31.3	333.6	198.2
ITC1	32	627.5	1724.7	1153.9	PL61	15	3.0	212.5	91.7
ITC3	32	1.6	10.6	6.6	PL62	15	0.0	42.6	19.0
ITC4	32	1041.9	3318.1	1940.1	PL63	15	0.0	26.2	10.8
ITF1	32	45.1	93.3	66.5	PT11	24	108.5	257.8	190.0
ITF2	32	9.0	42.8	26.9	PT15	24	3.3	7.2	5.3
ITF3	32	111.4	245.0	172.5	PT16	11	159.1	275.8	203.7
ITF4	32	6.1	17.6	11.4	PT17	11	30.9	101.0	55.9
ITF5	32	10.5	32.7	20.0	PT18	11	178.3	454.5	329.0
ITF6	32	26.5	54.4	34.7	RO11	15	606.5	1437.4	979.2
ITG1	32	0.7	26.1	7.6	RO12	15	382.7	794.0	546.8
ITG2	32	9.2	44.1	24.6	RO21	15	680.5	1981.4	1532.6
ITH3	32	1609.1	3387.6	2299.5	RO22	15	396.9	3431.4	1697.3
ITH4	32	397.5	1285.2	735.1	RO31	15	463.6	3007.1	1826.6
ITI1	32	142.1	388.8	261.6	RO32	15	13.9	188.5	95.3
ITI2	32	70.1	191.2	134.6	RO41	15	315.2	2056.2	1330.2
ITI4	32	137.7	248.7	196.8	RO42	15	674.6	1761.4	1149.4
NL11	17	0.0	9.3	2.3	SK01	15	0.0	77.8	40.5
NL12	17	0.0	6.3	1.5	SK02	15	356.0	958.5	620.3
NL13	17	1.2	22.9	6.8	SK03	15	13.0	100.2	45.0
NL21	17	2.6	23.7	12.4	SK04	15	41.0	124.1	70.3
NL22	17	7.9	43.5	24.3	TR10	10	1.9	184.9	23.3
NL34	17	1.9	8.3	5.1	TR21	10	17.7	32.1	24.1
NL41	17	20.6	140.1	84.8	TR22	10	22.0	39.9	31.5
NL42	17	12.0	82.7	51.1	TR31	10	11.0	24.3	16.4
PL11	15	7.1	80.8	34.8	TR32	10	77.1	155.6	99.1
PL12	15	11.8	185.2	78.1	TR33	10	14.2	125.1	55.3
PL21	15	16.6	94.2	52.2	TR41	10	40.4	99.4	51.4
PL22	15	12.4	111.4	65.8	TR42	10	364.9	463.9	428.1
PL31	15	7.5	126.7	59.0	TR52	10	1.9	79.9	17.4
PL32	15	19.6	74.8	49.1	TR61	10	9.2	74.6	34.6

Appendix 3 - Statistics of drought indices data set

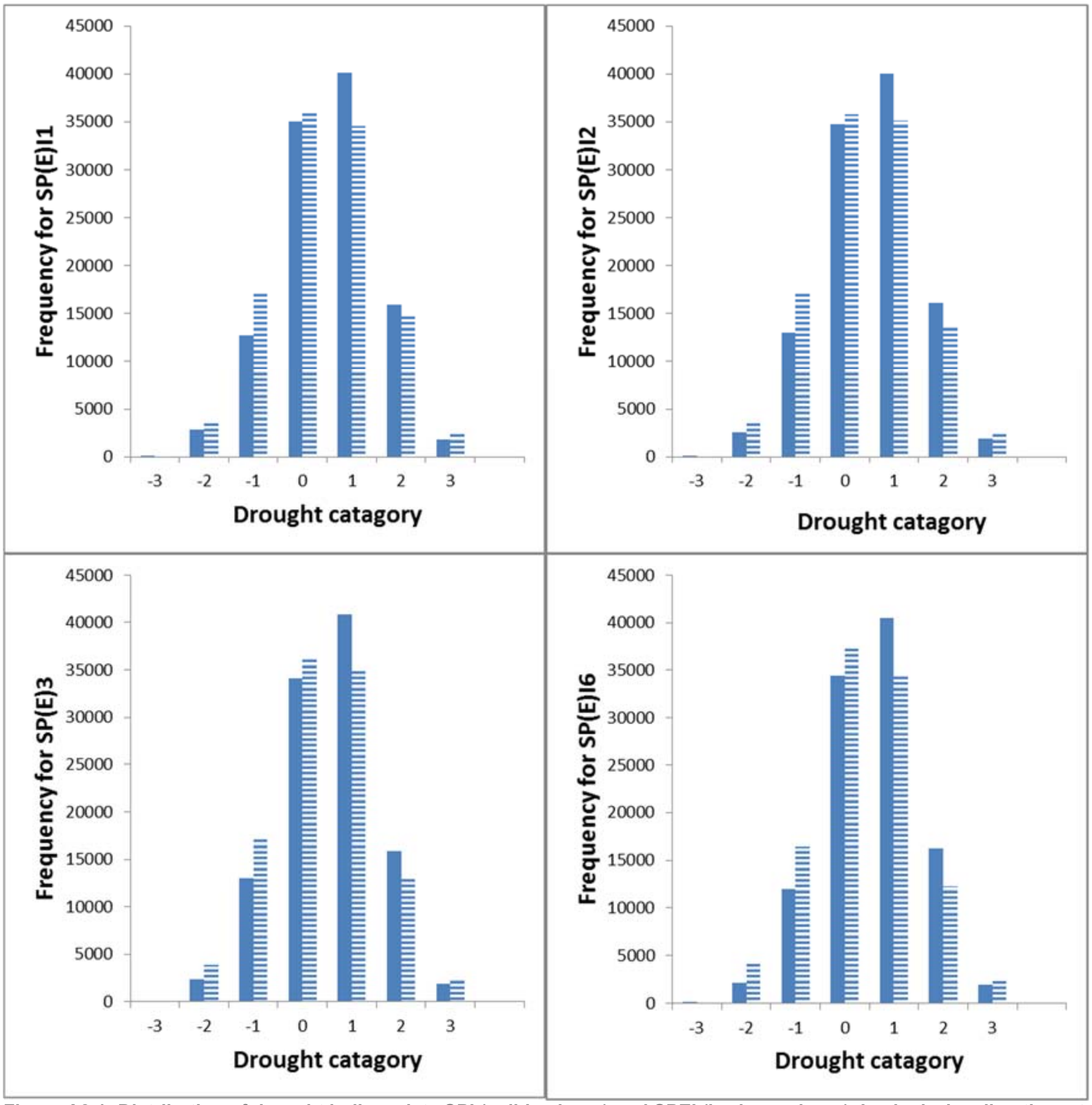

Figure A3.1: Distribution of drought indices data SPI (solid column) and SPEI (broken column). In clockwise direction, starting from upper left, we find SP(E)I1, 2, 3 and 6, respectively. SPEI finds more dry spells than SPI due to the temperature component in this index.

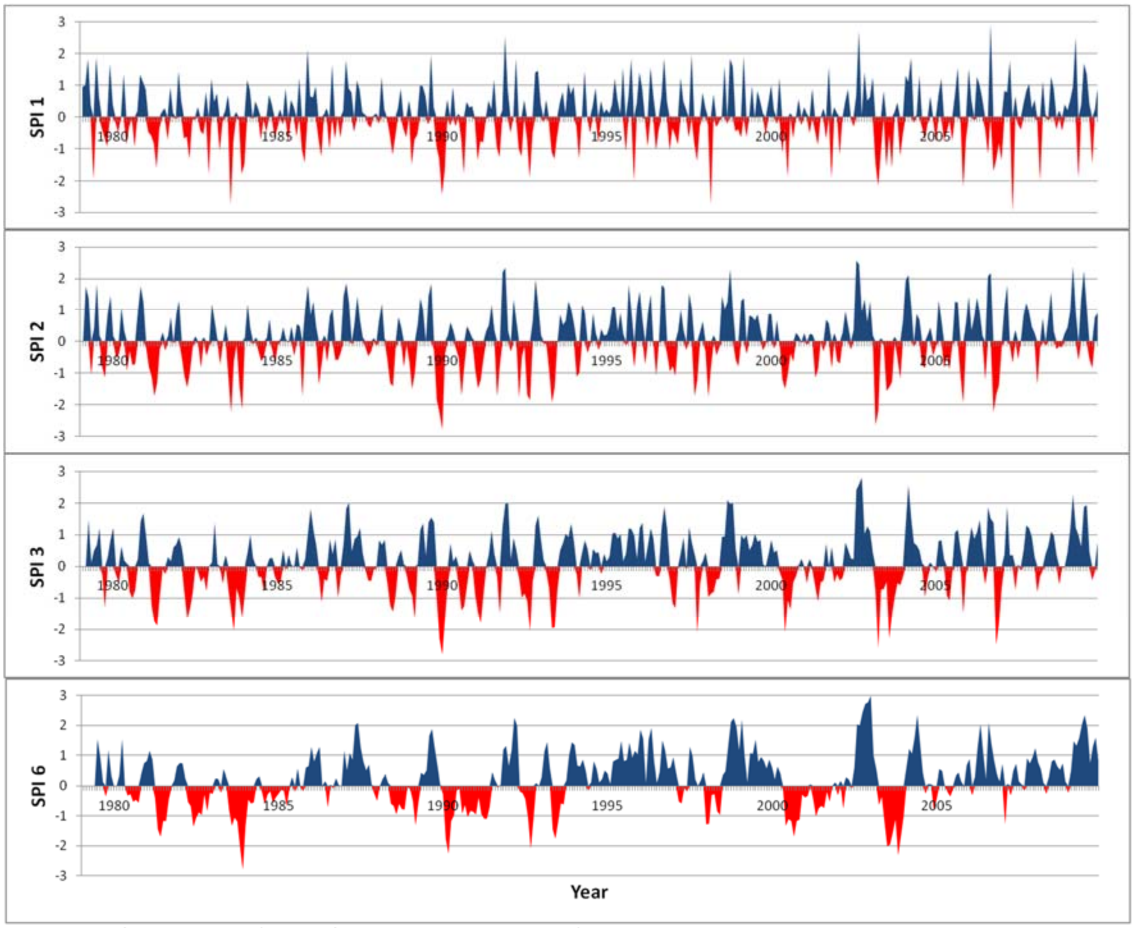

Figure A3.2: SPI1,2,3 and 6 for NUTS2 region AT11 in Austria for the 30-year data set (1979 - 2009). At higher accumulation periods the dry and wet spells get more concentrated and show a longer duration period resulting in fewer droughts/wet events.

Appendix 4 - Crop specific study area (NUTS2 regions)

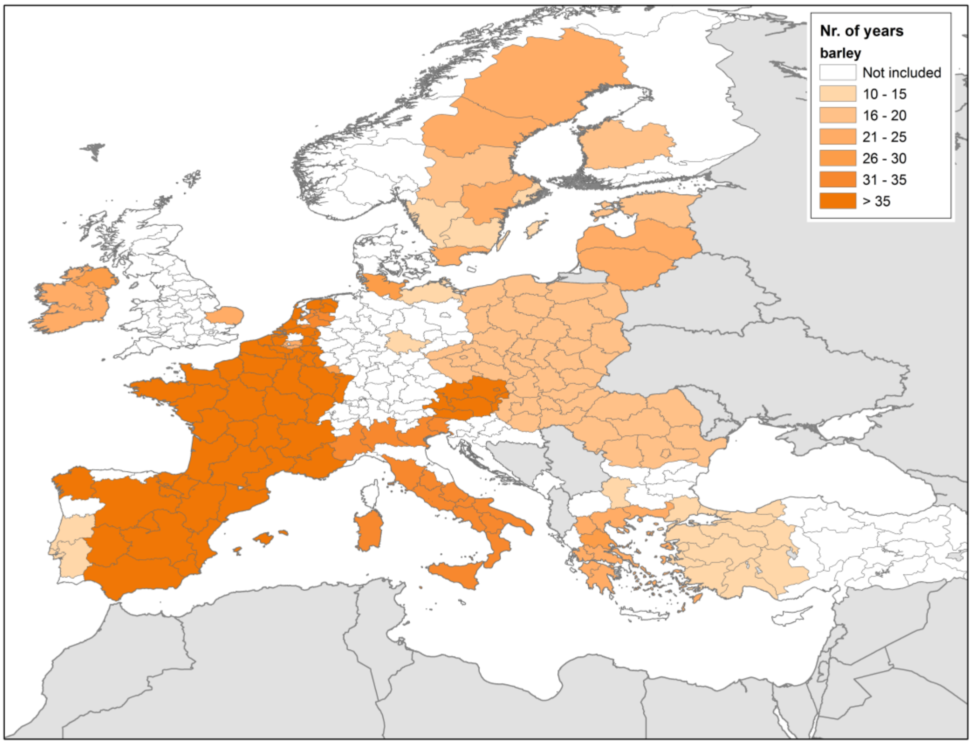

Figure A4.1: Numbers of years of crop yield data for barley. Austria contained the longest data set (39 years). For Belgium and the Netherlands most NUTS2 regions had 39 years of notification as well.

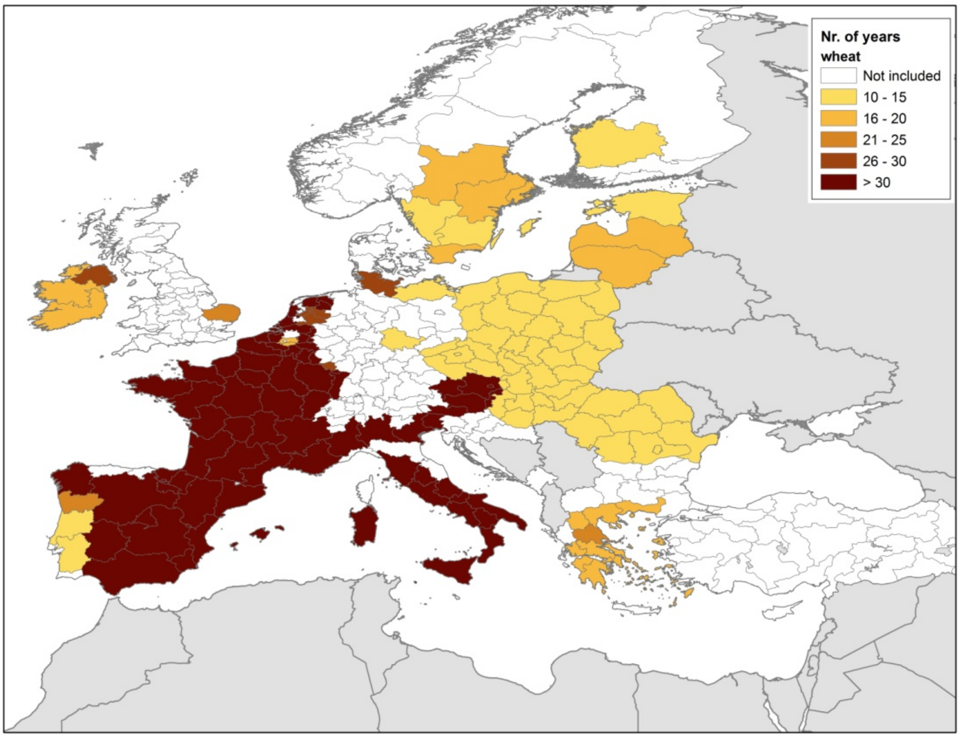

Figure A4.2: Numbers of years with crop yield data for wheat. Austria, the Netherlands and most regions in Belgium provided the longest data set (35 years).

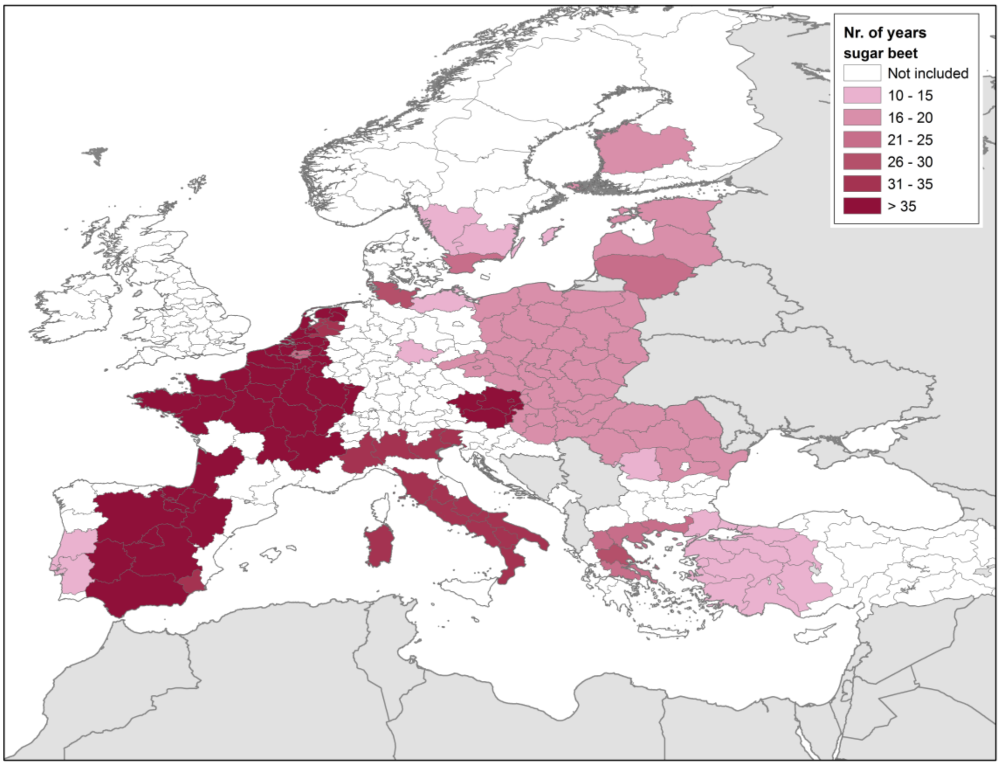

Figure A4.3: Numbers of years with crop yield data for sugar beet. Austria provided the longest data set (39 years), just like most regions in Belgium.

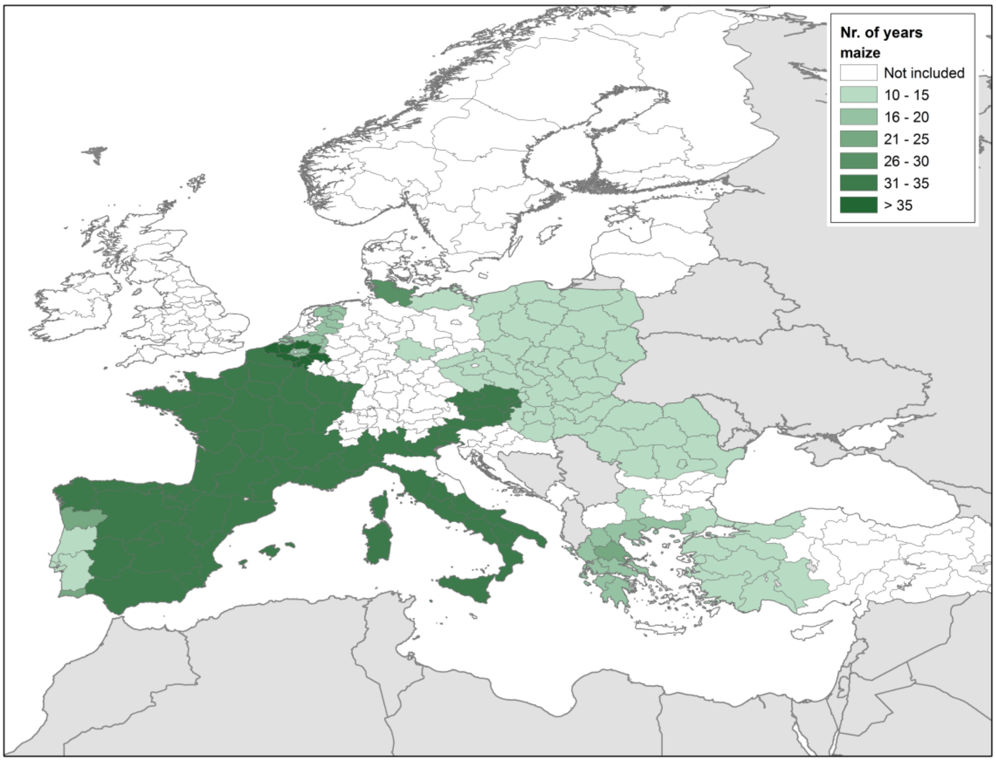

Figure A4.4: Numbers of years with crop yield data for maize. Most regions in Belgium provided the longest data set (36 years).

Appendix 5 - Results of SPEI statistical model

Table A5.1: Statistical yield change model that describes the relationship between the wheat yield anomaly and the SPEI for the moving average de-trended data set

Scale	Statistical model	R^2	N
Europe	-3,135 x **SPI3_10_P** + 2,631 x **SPI3_7** + 2,907 x **SPI2_4** - 3,025 x **SPI2_12_P** + 1,284 x **SPI1_1**	0.072	3432
Atlantic	-5,342 x **SPI3_12_P** - 2,974 x **SPI2_6** - 1,234 x **SPI1_8** - 1,181 x **SPI3_4**	0.189	994
Continental	4,307 x **SPI1_6** - 4,119 x **SPI2_12_P** + 3,628 x **SPI3_10_P** + 1,757 x **SPI1_1** + 1,389 x **SPI1_7**	0.133	1105
Mediterranean	9,733 x **SPI3_5** + 3,165 x **SPI2_2** + 2,272 x **SPI1_10_P** - 1,845 x **SPI3_9_P**	0.147	941

Table A5.2: Statistical yield change model that describes the relationship between the barley yield anomaly and the SPEI for the moving average de-trended data set

Scale	Statistical model	R^2	N
Europe	3,036 x **SPI3_7** + 2,459 x **SPI2_4** - 1,653 x **SPI1_8** -1,782 x **SPI1_12_P**	0.033	3631
Atlantic	-4,032 x **SPI3_6** + 4,849 x **SPI1_11_P** - 2,757 x **SPI3_1** + 1,752 x **SPI1_3** - 1,129 x **SPI1_8**	0.119	1013
Continental	4,629 x **SPI2_7** - 3,294 x **SPI2_12_P** + 1,788 x **SPI1_4** -1,79 x **SPI1_2** - 1,644 x **SPI3_9_P**	0.083	1115
Mediterranean	6,033 x **SPI3_5** - 3,925 x **SPI1_8** + 4,557 x **SPI2_2** + 3,025 x **SPI2_6**	0.088	1016

Table A5.3: Statistical yield change model that describes the relationship between the potato yield anomaly and the SPEI for the moving average de-trended data set

Scale	Statistical model	R^2	N
Europe	-2,725 x **SPI1_4** + 2,375 x **SPI3_8** - 1,828 x **SPI1_10**	0.031	3826
Atlantic	-5,385 x **SPI1_4** + 3,122 x **SPI1_8** - 3,622 x **SPI1_10** + 1,758 x **SPI1_6**	0.072	1103
Continental	-4,822 x **SPI2_4** + 4,286 x **SPI3_9** - 2,101 x **SPI1_10**	0.056	1054
Mediterranean	2,509 x **SPI1_3** - 2,416 x **SPI1_10** + 1,535 x **SPI3_8**	0.042	1121

Table A5.4: Statistical yield change model that describes the relationship between the sugar beet yield anomaly and the SPEI for the moving average de-trended data set

Scale	Statistical model	R^2	N
Europe	No significant model	-	2748
Atlantic	-5,939 x **SPI2_5**	0.007	812
Continental	5,761 x **SPI3_8** - 2,579 x **SPI1_3**	0.030	928
Mediterranean	-6,013 x **SPI1_1** + 5,684 x **SPI2_5**	0.012	684

Table A5.5: Statistical yield change model that describes the relationship between the maize yield anomaly and the SPEI for the moving average de-trended data set

Scale	Statistical model	R^2	N
Europe	8,127 x **SPI1_6** - 8,515 x **SPI2_10**	0.003	2835
Atlantic	-10,5 x **SPI3_5** + 6,643 x **SPI1_7**	0.023	766
Continental	30,454 x **SPI1_6**	0.007	765
Mediterranean	-8,978 x **SPI1_10**	0.006	1038

Table A5.6: Statistical yield change model that describes the relationship between the wheat yield anomaly and the SPEI for the linear regression de-trended data set

Scale	Statistical model	R^2	N
Europe	9,901 x **SPEI2_1**	0.004	1742
Atlantic	12,738 x **SPEI2_8** - 21,61 x **SPEI1_9_P** + 19,431 x **SPEI3_10_P**	0.031	807
Continental	43,953 x **SPEI2_1** + 22,132 x **SPEI1_9_P**	0.028	498
Mediterranean	7,306 x **SPEI3_3**	0.024	283

Table A5.7: Statistical yield change model that describes the relationship between the barley yield anomaly and the SPEI for the linear regression de-trended data set

Scale	Statistical model	R^2	N
Europe	3,212 x **SPEI2_3** + 2,93 x **SPEI1_11_P**	0.016	1424
Atlantic	8,795 x **SPEI3_9_P** + 7,259 x **SPEI1_9_P** - 4,229 x **SPEI3_6**	0.061	558
Continental	-3,213 x **SPEI3_2** + 2,602 x **SPEI3_6** - 2,358 x **SPEI2_12_P**	0.065	361
Mediterranean	8,117 x **SPEI3_5** + 6,226 x **SPEI3_1** - 3,816 x **SPEI1_8**	0.104	426

Table A5.8: Statistical yield change model that describes the relationship between the potato yield anomaly and the SPEI for the linear regression de-trended data set

Scale	Statistical model	R^2	N
Europe	5,36 x **SPEI1_8** - 5,656 x **SPEI1_4** + 4,457 x **SPEI1_3** - 3,145 x **SPEI2_6**	0.037	2642
Atlantic	-6,636 x **SPEI3_6** + 5,361 x **SPEI1_8**	0.026	771
Continental	11,166 x **SPEI2_8** - 11,539 x **SPEI3_6** + 7,815 x **SPEI1_3**	0.069	808
Mediterranean	-2,928 x **SPI2_10** + 2,38 x **SPI1_3** + 1,956 x **SPI1_8**	0.024	699

Table A5.9: Statistical yield change model that describes the relationship between the sugar beet yield anomaly and the SPEI for the linear regression de-trended data set

Scale	Statistical model	R^2	N
Europe	No significant model	-	877
Atlantic	No significant model	-	292
Continental	No significant model	-	305
Mediterranean	502,097 x **SPI2_3**	0.027	197

Table A5.10: Statistical yield change model that describes the relationship between the maize yield anomaly and the SPEI for the linear regression de-trended data set

Scale	Statistical model	R^2	N
Europe	No significant model	-	1839
Atlantic	12,414 x **SPEI2_8** + 15,251 x **SPEI1_10**	0.019	557
Continental	21,045 x **SPEI1_9**	0.010	661
Mediterranean	7,306 x **SPEI3_3**	0.024	516