Seventh Framework Programme

KBBE.2013.1.4-09

Improving the capacity of agro-meteorological crop modelling to integrate climatic variability and extreme weather events

MODelling vegetation response to EXTREMe Events

Project ID: 613817

Deliverable number: D5.1

Deliverable title: Evaluation of forecasts based on agro-climatic indicators

EC version: 1

Due date of deliverable	**30/04/2015 (18)**
Actual submission date	**28/04/2015 (18)**

Copyright © 2014, MODEXTREME Consortium

DOCUMENT INFO

1. Author(s)

Organization name lead contractor	**UNIMI**

Author	Organisation	e-mail
Valentina Pagani	**UNIMI**	**valentina.pagani@unimi.it**
Tommaso Guarneri	**UNIMI**	**tommi.guarneri@gmail.com**
Tommy Klein	**WBF-Agroscope**	**tommy.klein@alumni.ulg.ac.be**
Pierluigi Calanca	**WBF-Agroscope**	**pierluigi.calanca@agroscope.admin.ch**
Roberto Confalonieri	**UNIMI**	**roberto.confalonieri@unimi.it**

2. Revision history

Version	Date	Modified by	Comments
0	13/04/2015	Roberto Confalonieri	Starting version
1	28/04/2015	Roberto Confalonieri	After comments from Coordinator and co-coordinator

3. Dissemination level

PU	Public	☒
PP	Restricted to other program participants (including the Commission Service	☐
RE	Restricted to a group specified by the consortium (including the Commission Services)	☐
CO	Confidential, only for members of the consortium (excluding the Commission Services)	☐

Copyright © 2014, MODEXTREME Consortium

EXECUTIVE SUMMARY

Background	Different types of forecasting systems were developed in the last decades. The most sophisticated are based on biophysical crop simulation models; however, under specific conditions, statistical relationships between agro-climatic indicators and crop yields are able to explain a large part of the inter-annual variability in crop productions.
Objectives	The aim of this report was to evaluate the reliability of forecasting systems based on agro-climatic indicators for the main winter and summer crops and mown grasslands grown in Europe.
Methods	Five agro-climatic indicators considering the effects of drought and extreme temperatures on crop growth were used as regressors in statistical models to relate them to historical series of official crop yields from European countries. First, for each combination crop × country, the sub-set of indicators better explaining yield variability was identified. At a later stage, a leave-one-out cross validation procedure was applied to all the combinations crop × country where the indicator-based statistical models were able to capture a sufficient part of the yield variability. This led to quantify the reliability of forecasting systems based on agro-climatic indicators.
Results & implications	Results demonstrated the forecasting ability of agro-climatic indicators for some of the combinations crop × country. The best performances were obtained for winter cereals in Spain, where climatic indicators explained about 80-85% of yield variability after applying the cross-validation procedure. In general, indicator-based forecasting systems achieved better results especially in environments characterized by limiting thermal and pluviometric regimes.

Copyright © 2014, MODEXTREME Consortium

Table of contents

Copyright © 2014, MODEXTREME Consortium

Introduction

There is an increasing demand for timely and reliable crop yield forecasting systems in both developed and developing countries (Bouman, 1995). Early warnings in case of poor crop harvests allow indeed governments and other stakeholders to assure food imports and regulate agricultural markets (Supit, 1997; Bannayan and Crout, 1999).

In the last decades, a variety of forecasting systems were developed. The first methods were based on surveys or crop scouting (Bannayan and Crout, 1999); these approaches were replaced since the 1990s by more objective and sound techniques (Bauman et al., 1997), based on the single or integrated use of agro-climatic indicators, remote-sensing information, and crop models. The most sophisticated forecasting methods are based on crop simulation models. An example is represented by the MARS system, mainly based on the WOFOST model (Van Keulen and Wolf, 1986), which was developed by the European Commission in order to provide timely production forecasts for the main food crops at European level (Vossen and Rijks, 1995). However, in specific contexts where crop production fluctuations are driven by few main factors, statistical models based on relationships between a few, relevant agro-climatic indicators and crop yields can be able to accurately explain the inter-annual crop yield variability, and thus to reliably forecast crop yields (Balaghi et al., 2012). Existing response functions to weather factors were often developed for conditions of good adaptation of plants and were designed targeting environments characterized by favourable – or mildly sub-favourable – temperature and rainfall regimes.

In recent years, many climatic and agro-climatic indices were developed and related to the impact of extreme weather events (e.g., drought, extreme temperatures) on agricultural productions (e.g., Confalonieri et al., 2010; Trnka et al., 2011; Rivington et al., 2013). These metrics can be very simple, like those based on counts, i.e., the number of times a phenomenon occurs, sums (e.g., thermal and rainfall sums), or more complex, like those considering plant susceptibility to an extreme event in different moments during the crop cycle. The use of agro-climatic indicators focusing on extreme events to predict yields allows to identify the environments where extreme factors highly influence inter-annual variability of crop production.

The aim of this work was:

- to evaluate the potential for forecasting crop yields based on spatially aggregated temperature and drought indicators for the main winter and summer crops and for mown grasslands in all European countries where the specific crop is cultivated;
- to identify and analyse the combinations crop × country where forecasting systems based on agro-climatic indicators present sufficient reliability in case of extreme events.

Copyright © 2014, MODEXTREME Consortium

1. Materials and methods

1.1. Studied crops

The studied crops were divided in three groups (i.e., cereals, other crops and mown grasslands) as shown in *Table 1*. The most representative summer and winter annual crops at European level were indeed analysed; moreover, permanent mown grasslands were considered, by assuming a growing season starting in spring and ending in autumn.

Table 1. *List of the main annual/perennial and summer/winter crops cultivated in Europe.*

		summer crops	***winter crops***
Annual crops	***Cereals***	maize rice	wheat barley rye triticale
	Other crops	sunflower potatoes sugar beet	rapeseed
Perennial crops	***Mown Grasslands***	grasses, legumes, forbs	

1.2. Agro-climatic indicators

Five agro-climatic indicators for drought and extreme temperatures (*Table 2*) were selected during the activities performed within MODEXTREME WP1 (see MS1 and D1.1).

Table 2. *List of climatic indices selected for the forecasting system.*

Type of event	Index	Definition
Heat	Tmaxcr	Number of days with Tmax higher than a fixed threshold
Frost	Tmincr	Number of days with Tmin lower than a fixed threshold
Drought	ARIDmean	Average value of the Agricultural Reference Index for Drought
Drought	ARIDcr	Number of days with ARID higher than a fixed threshold
Drought	Fu	Value of Fu drought index

The indicators for heat and frost are simple counts of days with maximum/minimum daily temperature above/below a fixed threshold (Rivington et al., 2013).

The effect of water shortage was evaluated using the ARID – Agricultural Reference Index for Drought – (Woli et al., 2012) and Fu indicators (Fu, 1981; Zhang et al., 2008).

The former is a simple, general, soil-plant-atmosphere metric (Narasimhan and Srinivasan, 2005), calculated according to *Equation 1*:

Copyright © 2014, MODEXTREME Consortium

$$ARID = 1 - \frac{T_a}{T_p} \qquad \textbf{Eq. 1}$$

where T_p is the potential crop transpiration; T_a is the minimum between T_p and crop water uptake, which in turn depends on the maximum fraction of available water extracted in a day, on the rooting depth and on the plant available water. ARID ranges from 0 (no water deficit) to 1 (maximum water deficit).

The second drought indicator (Fu) is based on the assumptions for which the equilibrium water balance is controlled by water availability and atmospheric demand (*Equation 2*):

$$FU = -\frac{\sum P}{\sum ET_0} + \left[1 + \left(\frac{\sum P}{\sum ET_0}\right)^{w}\right]^{(1/w)} \qquad \textbf{Eq. 2}$$

where $\sum P$ and $\sum ET_0$ are cumulated rainfall and reference evapotranspiration; w is a parameter regulating the slope of the curve.

The values for the five climatic indicators were here calculated using the weather data from the E-OBS database (Haylock et al., 2008), characterized by a spatial resolution of 25 × 25 km.

1.3. Development of the forecasting system

The forecasting method is based – for each combination crop × country – on the statistical post-processing of agro-climatic indicators and time series of official yields.

In the following paragraphs the inputs data required by the forecasting system are shown, followed by a description of the steps required to perform the statistical analysis.

1.3.1. Input data

Official statistics: historical data of crop production, cultivated area and yields for each combination crop × country were downloaded from the FAOSTAT website (http://faostat3.fao.org/home/) for the last 25 years.

Crop masks: the aggregation of the climatic indicators at national level was performed using the crop masks proposed by Monfreda et al. (2008). In particular, the geographic distribution of the three studied groups of crops (i.e., cereals, other crops and grasslands) was considered (*Figure 1a-b-c*).

Crop calendars: crop calendars from the MARS database were used.

Copyright © 2014, MODEXTREME Consortium

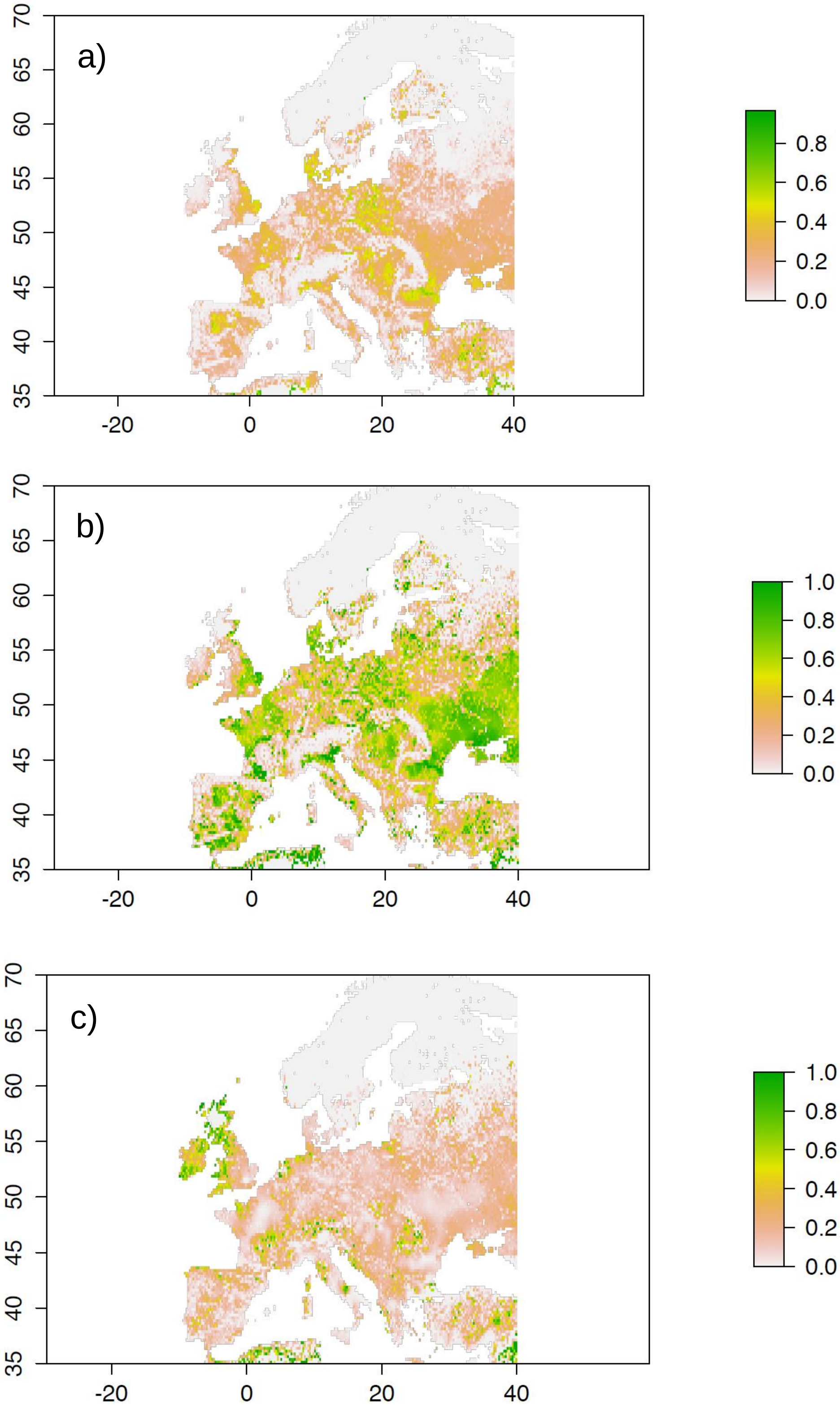

Figure 1*. Percentage cover for a) cereal crops; b) other crops; c) grasslands in Europe (Monfreda et al., 2008).*

Copyright © 2014, MODEXTREME Consortium

1.3.2. Statistical analysis

The agro-climatic indicators were calculated for each of the 25 × 25 km cells for the whole Europe and then temporally and spatially aggregated.

- ☐ ***Temporal aggregation***: for winter crops, indicators were calculated until maturity, as well as until two and four ten-day periods before maturity. For summer crops, they were calculated until maturity and until three and seven ten-day periods before maturity. This allowed to analyse the performance of the forecasting systems in different moments during the crop cycle. For both winter and summer crops, the three moments when the forecasting events were triggered correspond to flowering, maturity, and the ten-day period in the mid of the reproductive phase.
- ☐ ***Spatial aggregation***: the indicators were then aggregated at country level on the basis of the percentage of crop presence in each 25 × 25 km cell (*Figure 1*). In particular, indicators referred to winter crops were aggregated using the cereals mask for wheat, barley, rye and triticale, whereas the mask for "other crops" was used for rapeseed. For summer crops, indicators were aggregated on the basis of the cereals mask for maize and rice, the "other crops" mask for sunflower, potatoes and sugar beet; the grasslands mask was instead used for pastures.

The agro-climatic indicators aggregated at national level for the three ten-day periods of analysis were post-processed together with the available time series of official yields for each combination crop × country, assuming the indicators and the official yields, respectively, as the independent and dependent variables of a multiple linear regression.

The steps of the statistical post-processing for each combination crop × country are described below:

a) identification of possible **technological trends** in historical series of yield data, i.e., a linear or quadratic trend due to the introduction of technological innovations (e.g., high-performing varieties, new agro-chemicals) or economic policies leading to a yield increase independent from seasonal variability in weather variables (*Section 2.1*). In case of significant trends, historical yield data were detrended before further analysis;

b) application of **multiple linear regressions** on the available time series using the "best subsets regression" method, based on the comparison among the best-fitting models that contain one, two, three and four agro-climatic indicators as regressors. Final result is a number of models characterized by different summary statistics (e.g., R^2, adjusted R^2, RMSE, Mallows Cp,..). In particular, results shown in *Section 2.1* are related to the regression models for the sets of indicators presenting – for each combination crop × country – the most satisfactory values of (i) coefficient of determination (R^2; *Equation 3*), representing the percentage of the variance explained by the model and (ii) adjusted R^2 (*Equation 4*), which accounts for the effect of increasing number of regressors.

$$R^2 = \frac{\sum_{i=1}^{n}(S_i - \bar{M})^2}{\sum_{i=1}^{n}(M_i - \bar{M})^2} \qquad \textbf{\textit{Eq. 3}}$$

where M_i is the official yield in the *i*-th year, S_i is the forecasted yield in the *i*-th year, $\bar{M}$ is the average of official yields, n is the number of observations.

Copyright © 2014, MODEXTREME Consortium

$$R^2{}_{adj} = 1 - (1 - R^2)\frac{n-1}{n-p-1} \qquad \textbf{\textit{Eq. 4}}$$

where p is the number of independent variables of the regression model.

A supervised selection procedure based on R^2 and on the importance of the crop in the country was carried out in order to identify the combinations crop × country where the agro-climatic indicators were able to explain a relevant part of year-to-year yield variability.

c) **leave-one-out cross-validation** procedure on the historical series of yield data, using *n* times *n*-1 years to forecast the remaining one, to quantify the reliability of the system for forecasting purposes, i.e., its accuracy to predict yield values not used to construct the regression model.

In particular, the following steps were carried out:

- exclusion of possible technological trends from the official yields;
- construction of multiple regressions between the de-trended official yields and climatic indices, applying the leave-one-out cross-validation;
- selection of the statistical model based on the sets of agro-climatic indicators with the highest "forecasting capability";
- addition of the technological trend to the series of forecasted yields;
- comparison between official and forecasted yields through the calculation of some fitting indices, i.e., Relative Root Mean Square Error – RRMSE (Jorgensen et al., 1986 - *Equation 5*; min/opt = 0, max = +∞), Modelling Efficiency – EF (Nash and Sutcliffe, 1970 - *Equation 6*; min/opt = 1, max = +∞), Coefficient of Residual Mass – CRM (Loague and Green, 1991 – *Equation 7*; min = -∞, opt = 0, max = +∞), Coefficient of determination – R^2(*Equation 3*).

$$RRMSE = 100 \cdot \frac{\sqrt{\frac{\sum_{i=1}^{n}(S_i - M_i)^2}{n}}}{\bar{M}} \qquad \textbf{\textit{Eq. 5}}$$

$$EF = 1 - \frac{\sum_{i=1}^{n}(S_i - M_i)^2}{\sum_{i=1}^{n}(M_i - \bar{M})^2} \qquad \textbf{\textit{Eq. 6}}$$

$$CRM = \frac{\sum_{i=1}^{n} M_i - \sum_{i=1}^{n} S_i}{\sum_{i=1}^{n} M_i} \qquad \textbf{\textit{Eq. 7}}$$

Copyright © 2014, MODEXTREME Consortium

2. Results

2.1. Technological trend and linear multiple regressions

Table 3 to *Table* 12 show the results of steps **a)** and **b)** described in *Section 1.3.2*. In particular, for each combination crop × country, tables present the percentage of yield variability described (i) by the technological trend, (ii) by the multiple linear regression model, and (iii) by the total forecasting system (trend + multiple linear regression).

The statistical models were applied using the values of the indicators calculated for three different moments, running from sowing to three different stages of the crop cycle (see *Section 1.3.2*). The countries where the climatic indicators were able to explain a relevant part of the inter-annual variability in crop yields are highlighted in bold. For these cases, the ten-day period for which the highest forecasting capability was achieved is highlighted in the same way.

Results presented in the tables show that the forecasting capability of agro-climatic indicators is higher in countries located in central and southern Europe, with exceptions represented by mown grasslands in Germany and potatoes in Poland). In particular – in light of the fact that three out of the five indicators used are related with plant available water – indicators showed satisfactory performances in Mediterranean countries (i.e., Spain, Italy and Croatia), characterized by dry summers and temperate-rainy winters.

For most of the combinations crop × country highlighted in bold in Tables 3 to 13, the technological trend is not remarkable and a large part of interannual yield variability is explained by the agro-climatic indicators, with the exception of maize in Italy (*Table 7)*, sunflower in Bulgaria (*Table 9*), rapeseed in Romania (*Table*) and sugar beet in Croatia and Italy (*Table 11*), where the technological trend explains, alone, more than 40% of yield variability in the last 20 years.

A final consideration derives from the forecasting capability of the agro-climatic based system for the three ten-day periods for which the forecasting events were triggered. As expected, in most cases the system reliability increases while approaching maturity.

Copyright © 2014, MODEXTREME Consortium

Table 3. *Percentage of **WHEAT** inter-annual yields variability (R^2) in European countries explained by (i) the technological trend; (ii) the regression model including the best combination of climatic indices and (iii) the sum of technological trend and climatic indices, at 15th, 13th and 11th ten-day period of the year.*

			15th ten-day period		***13th ten-day period***		***11th ten-day period***	
Country	**Period**	**Trend**	**Model**	**Total**	**Model**	**Total**	**Model**	**Total**
Austria	1990-2013	0	0.43	0.43	0.25	0.25	0.01	0.01
Belgium	2000-2013	0	0.48	0.48	0.38	0.38	0.09	0.09
Bulgaria	1990-2013	0.4	0.09	0.49	0.08	0.48	0.16	0.56
Croatia	1992-2013	0.4	0.44	0.84	0.43	0.83	0.4	0.8
Denmark	1990-2013	0	0.08	0.08	0.08	0.08	0.1	0.1
Czech R.	1993-2013	0.26	0.33	0.59	0.17	0.43	0.01	0.27
Estonia	1992-2013	0.64	0.03	0.67	0.02	0.66	0.02	0.66
Finland	1990-2013	0	0.07	0.07	0.13	0.13	0.1	0.1
France	1990-2013	0	0.41	0.41	0.18	0.18	0.09	0.09
Greece	1990-2013	0	0.26	0.26	0.26	0.26	0.27	0.27
Germany	1990-2013	0.32	0.22	0.54	0.21	0.53	0.09	0.41
Hungary	1990-2013	0	0.46	0.46	0.39	0.39	0.21	0.21
Ireland	1990-2013	0	0.1	0.1	0.1	0.1	0.07	0.07
Italy	1990-2013	0.45	0.3	0.75	0.31	0.76	0.26	0.71
Latvia	1992-2013	0.73	0.06	0.79	0.07	0.8	0.08	0.81
Lithuania	1992-2013	0.55	0.06	0.61	0.09	0.64	0.06	0.61
Netherlands	1992-2013	0	0.27	0.27	0.28	0.28	0.33	0.33
Poland	1990-2013	0.34	0.15	0.49	0.15	0.49	0.22	0.56
Portugal	1990-2013	0	0.23	0.23	0.21	0.21	0.19	0.19
Romania	1990-2013	0	0.34	0.34	0.27	0.27	0.09	0.09
Slovakia	1993-2013	0	0.56	0.56	0.44	0.44	0.05	0.05
Slovenia	**1992-2013**	**0.24**	**0.57**	**0.81**	0.24	0.48	0.12	0.36
Spain	**1990-2013**	**0.31**	**0.58**	**0.89**	0.5	0.81	0.37	0.68
Sweden	1990-2013	0	0.18	0.18	0.21	0.21	0.29	0.29
United Kingdom,	1990-2013	0.38	0.05	0.43	0.05	0.43	0.01	0.39

Copyright © 2014, MODEXTREME Consortium

Table 4. *Percentage of* ***BARLEY*** *inter-annual yields variability (R^2) in European countries explained by (i) the technological trend; (ii) the regression model including the best combination of climatic indices and (iii) the sum of technological trend and climatic indices, at 15th, 13th and 11th ten-day period of the year.*

			15th ten-day period		***13th ten-day period***		***11th ten-day period***	
Country	**Period**	**Trend**	**Model**	**Total**	**Model**	**Total**	**Model**	**Total**
Austria	1990-2013	0	0.38	0.38	0.2	0.2	0.06	0.06
Belgium	2000-2013	0	0.34	0.34	0.15	0.15	0.13	0.13
Bulgaria	1990-2013	0.4	0.15	0.55	0.14	0.54	0.12	0.52
Croatia	1992-2013	0.41	0.39	0.8	0.37	0.78	0.36	0.77
Denmark	1990-2013	0	0.07	0.07	0.05	0.05	0.04	0.04
Czech R.	1993-2013	0.31	0.16	0.47	0.09	0.4	0	0.31
Estonia	1992-2013	0.65	0.01	0.66	0.01	0.66	0.01	0.66
France	1990-2013	0.24	0.28	0.52	0.2	0.44	0.13	0.37
Greece	1990-2013	0	0.4	0.4	0.34	0.34	0.36	0.36
Germany	1990-2013	0.3	0.3	0.6	0.34	0.64	0.08	0.38
Hungary	1990-2013	0	0.33	0.33	0.26	0.26	0.21	0.21
Ireland	1990-2013	0.37	0.12	0.49	0.1	0.47	0.05	0.42
Italy	**1990-2013**	**0**	**0.75**	**0.75**	0.57	0.57	0.38	0.38
Latvia	1992-2013	0.76	0.02	0.78	0.08	0.84	0.02	0.78
Lithuania	1992-2013	0.59	0.01	0.6	0	0.59	0	0.59
Netherlands	1990-2013	0.22	0.39	0.61	0.39	0.61	0.21	0.43
Poland	1990-2013	0	0.12	0.12	0.05	0.05	0.13	0.13
Portugal	1990-2012	0	0.28	0.28	0.3	0.3	0.28	0.28
Romania	1990-2013	0	0.22	0.22	0.28	0.28	0.12	0.12
Slovakia	1993-2013	0	0.35	0.35	0.14	0.14	0.06	0.06
Slovenia	1992-2013	0.48	0.31	0.79	0.16	0.64	0.02	0.5
Spain	**1990-2013**	**0**	**0.8**	**0.8**	0.6	0.6	0.45	0.45
Sweden	1990-2013	0	0.13	0.13	0.26	0.26	0.24	0.24
United Kingdom	1990-2013	0	0.24	0.24	0.28	0.28	0.25	0.25

Copyright © 2014, MODEXTREME Consortium

Table 5. *Percentage of **RYE** inter-annual yields variability (R^2) in European countries explained by (i) the technological trend; (ii) the regression model including the best combination of climatic indices and (iii) the sum of technological trend and climatic indices, at 15th, 13th and 11th ten-day period of the year.*

			15th ten-day period		***13th ten-day period***		***11th ten-day period***	
Country	**Period**	**Trend**	**Model**	**Total**	**Model**	**Total**	**Model**	**Total**
Austria	1990-2013	0	0.3	0.3	0.33	0.33	0.26	0.26
Bulgaria	1990-2013	0	0.31	0.31	0.32	0.32	0.18	0.18
Denmark	1990-2013	0	0.04	0.04	0	0	0.01	0.01
Czech R.	1993-2013	0.42	0.09	0.51	0.08	0.5	0.07	0.49
Estonia	1992-2013	0.24	0.28	0.52	0.25	0.49	0.43	0.67
Finland	1990-2013	0.57	0.02	0.59	0.04	0.61	0.06	0.63
France	1990-2013	0.61	0.1	0.71	0.07	0.68	0.07	0.68
Greece	1990-2013	0	0.47	0.47	0.5	0.5	0.44	0.44
Germany	1990-2013	0.28	0.11	0.39	0.24	0.52	0.06	0.34
Hungary	1990-2013	0	0.37	0.37	0.34	0.34	0.13	0.13
Latvia	1992-2013	0.47	0.17	0.64	0.16	0.63	0.17	0.64
Lithuania	1992-2013	0.26	0.14	0.4	0.1	0.36	0.1	0.36
Poland	1990-2013	0	0.13	0.13	0.04	0.04	0.03	0.03
Portugal	1990-2013	0	0.33	0.33	0.33	0.33	0.28	0.28
Slovakia	1993-2013	0	0.37	0.37	0.06	0.06	0.05	0.05
Spain	**1990-2013**	**0.27**	**0.49**	**0.76**	0.21	0.48	0.11	0.38
Sweden	1990-2013	0.54	0.15	0.69	0.15	0.69	0.11	0.65

Table 6. *Percentage of **TRITICALE** inter-annual yields variability (R^2) in European countries explained by (i) the technological trend; (ii) the regression model including the best combination of climatic indices and (iii) the sum of technological trend and climatic indices, at 15th, 13th and 11th ten-day period of the year.*

			15th ten-day period		***13th ten-day period***		***11th ten-day period***	
Country	**Period**	**Trend**	**Model**	**Total**	**Model**	**Total**	**Model**	**Total**
Austria	1995-2013	0	0.38	0.38	0.46	0.46	0.36	0.36
Bulgaria	2001-2013	0	0.11	0.11	0.38	0.38	0.11	0.11
Denmark	1997-2013	0	0.35	0.35	0.24	0.24	0.43	0.43
Czech R.	1993-2013	0	0.11	0.11	0.11	0.11	0.11	0.11
France	1990-2013	0.4	0.25	0.65	0.1	0.5	0.07	0.47
Germany	1990-2013	0	0.09	0.09	0.16	0.16	0.09	0.09
Hungary	1990-2013	0	0.43	0.43	0.39	0.39	0.25	0.25
Lithuania	1993-2013	0.27	0.07	0.34	0.08	0.35	0.07	0.34
Poland	1990-2013	0	0.15	0.15	0.08	0.08	0.14	0.14
Portugal	1990-2013	0	0.19	0.19	0.22	0.22	0.16	0.16
Romania	**2003-2013**	**0**	**0.77**	**0.77**	0.66	0.66	0.31	0.31
Slovakia	1993-2013	0	0.34	0.34	0.19	0.19	0.008	0.008
Spain	1990-2013	0	0.3	0.3	0.37	0.37	0.44	0.44
Sweden	1995-2013	0	0.11	0.11	0.11	0.11	0.12	0.12
United Kingdom	1990-2013	0.51	0.06	0.57	0.02	0.53	0.04	0.55

Copyright © 2014, MODEXTREME Consortium

Table 7. *Percentage of MAIZE inter-annual yields variability (R^2) in European countries explained by (i) the technological trend; (ii) the regression model including the best combination of climatic indices and (iii) the sum of technological trend and climatic indices, at 27th, 24th and 20th ten-day period of the year.*

			27th ten-day period		***24th ten-day period***		***20th ten-day period***	
Country	**Period**	**Trend**	**Model**	**Total**	**Model**	**Total**	**Model**	**Total**
Austria	1990-2013	0.72	0.18	0.9	0.18	0.9	0.05	0.77
Belgium	2000-2013	0	0.74	0.74	0.76	0.76	0.7	0.7
Bulgaria	1990-2013	0	0.49	0.49	0.58	0.58	0.49	0.49
Croatia	**1992-2013**	**0.25**	0.6	0.85	0.61	0.86	**0.64**	**0.89**
Czech R.	1993-2013	0.49	0.22	0.71	0.23	0.72	0.21	0.7
France	1990-2013	0.51	0.37	0.88	0.38	0.89	0.16	0.67
Greece	1990-2013	0.5	0.17	0.67	0.15	0.65	0.13	0.63
Germany	1990-2013	0.71	0.21	0.92	0.2	0.91	0.13	0.84
Hungary	1990-2013	0	0.57	0.57	0.69	0.69	0.41	0.41
Italy	**1990-2013**	**0.38**	0.43	0.81	**0.44**	**0.82**	0.44	0.82
Netherlands	1992-2013	0.54	0.07	0.61	0.06	0.6	0.08	0.62
Poland	1990-2013	0.48	0.32	0.8	0.34	0.82	0.39	0.87
Portugal	1990-2013	0.78	0.07	0.85	0.06	0.84	0.05	0.83
Romania	1990-2013	0	0.53	0.53	0.67	0.67	0.45	0.45
Slovakia	1993-2013	0	0.44	0.44	0.58	0.58	0.6	0.6
Slovenia	1992-2013	0.46	0.38	0.84	0.38	0.84	0.2	0.66
Spain	1990-2013	0.88	0.02	0.9	0.03	0.91	0.01	0.89

Table 8. *Percentage of **RICE** inter-annual yields variability (R^2) in European countries explained by (i) the technological trend; (ii) the regression model including the best combination of climatic indices and (iii) the sum of technological trend and climatic indices, at 27th, 24th and 20th ten-day period of the year.*

			27th ten-day period		***24th ten-day period***		***20th ten-day period***	
Country	**Period**	**Trend**	**Model**	**Total**	**Model**	**Total**	**Model**	**Total**
Bulgaria	1990-2013	0.64	0.05	0.69	0.06	0.7	0.07	0.71
France	1990-2013	0	0.2	0.2	0.12	0.12	0.15	0.15
Greece	1990-2013	0	0.1	0.1	0.11	0.11	0.18	0.18
Hungary	1990-2013	0.25	0.24	0.49	0.22	0.47	0.2	0.45
Italy	1990-2012	0.32	0.02	0.34	0.01	0.33	0.02	0.34
Portugal	1990-2013	0.67	0.06	0.73	0.05	0.72	0.06	0.73
Romania	1990-2013	0.48	0.06	0.54	0.04	0.52	0.09	0.57
Spain	1990-2013	0.6	0.03	0.63	0.08	0.68	0.09	0.69

Copyright © 2014, MODEXTREME Consortium

Table 9. *Percentage of* ***SUNFLOWER*** *inter-annual yields variability (R^2) in European countries explained by (i) the technological trend; (ii) the regression model including the best combination of climatic indices and (iii) the sum of technological trend and climatic indices, at 27th, 24th and 20th ten-day period of the year.*

			27th ten-day period		*24th ten-day period*		*20th ten-day period*	
Country	**Period**	**Trend**	**Model**	**Total**	**Model**	**Total**	**Model**	**Total**
Austria	1990-2013	0	0.23	0.23	0.11	0.11	0.3	0.3
Bulgaria	**1990-2013**	**0.6**	**0.31**	**0.91**	0.29	0.89	0.24	0.84
Croatia	1992-2013	0.38	0.34	0.72	0.3	0.68	0.25	0.63
Czech R.	1993-2013	0	0.45	0.45	0.32	0.32	0.59	0.59
France	1990-2013	0.17	0.44	0.61	0.39	0.56	0.36	0.53
Greece	1990-2013	0.68	0.03	0.71	0.07	0.75	0.08	0.76
Germany	1990-2013	0	0.27	0.27	0.41	0.41	0.18	0.18
Hungary	1990-2013	0.37	0.26	0.63	0.27	0.64	0.33	0.7
Italy	**1990-2013**	**0**	0.59	0.59	**0.63**	**0.63**	0.59	0.59
Portugal	1990-2013	0	0.18	0.18	0.2	0.2	0.22	0.22
Romania	1990-2013	0	0.24	0.24	0.21	0.21	0.22	0.22
Slovakia	1993-2013	0.41	0.15	0.56	0.19	0.6	0.31	0.72
Spain	1990-2013	0	0.47	0.47	0.51	0.51	0.49	0.49

Table 10. *Percentage of* ***RAPESEED*** *inter-annual yields variability (R^2) in European countries explained by (i) the technological trend; (ii) the regression model including the best combination of climatic indices and (iii) the sum of technological trend and climatic indices, at 15th, 13th and 20th ten-day period of the year.*

			15th ten-day period		*13th ten-day period*		*11th ten-day period*	
Country	**Period**	**Trend**	**Model**	**Total**	**Model**	**Total**	**Model**	**Total**
Austria	1990-2013	0	0.28	0.28	0.3	0.3	0.11	0.11
Belgium	2000-2013	0.45	0.21	0.66	0.12	0.57	0.06	0.51
Bulgaria	1993-2013	0.67	0.02	0.69	0.09	0.76	0.03	0.7
Denmark	1990-2013	0.65	0.03	0.68	0.01	0.66	0.01	0.66
Czech R.	1993-2013	0	0.29	0.29	0.32	0.32	0.26	0.26
Estonia	1994-2013	0.48	0.31	0.79	0.03	0.51	0.04	0.52
Finland	1990-2013	0.33	0.22	0.55	0.06	0.39	0.03	0.36
France	1990-2013	0.23	0.12	0.35	0.16	0.39	0.21	0.44
Germany	1990-2013	0.41	0.23	0.64	0.27	0.68	0.16	0.57
Hungary	1990-2013	0.5	0.18	0.68	0.17	0.67	0.12	0.62
Ireland	1990-2013	0.45	0.05	0.5	0.01	0.46	0	0.45
Italy	1990-2013	0.71	0.06	0.77	0.07	0.78	0.07	0.78
Latvia	1992-2013	0.7	0.04	0.74	0.06	0.76	0.01	0.71
Lithuania	1992-2013	0.33	0.02	0.35	0.06	0.39	0.05	0.38
Poland	1990-2013	0.35	0.31	0.66	0.16	0.51	0.14	0.49
Romania	**1990-2013**	**0.43**	0.31	0.74	**0.37**	**0.8**	0.16	0.59
Slovakia	1993-2013	0	0.34	0.34	0.44	0.44	0.16	0.16
Spain	1990-2013	0.33	0.23	0.56	0.2	0.53	0.17	0.5
Sweden	1990-2013	0.54	0.3	0.84	0.28	0.82	0.13	0.67
United Kingdom	1990-2013	0.35	0.24	0.59	0.25	0.6	0.15	0.5

Copyright © 2014, MODEXTREME Consortium

Table 10. *Percentage of* ***POTATOES*** *inter-annual yields variability (R^2) in European countries explained by (i) the technological trend; (ii) the regression model including the best combination of climatic indices and (iii) the sum of technological trend and climatic indices, at 27th, 24th and 20th ten-day period of the year.*

			27th ten-day period		*24th ten-day period*		*20th ten-day period*	
Country	**Period**	**Trend**	**Model**	**Total**	**Model**	**Total**	**Model**	**Total**
Austria	1990-2013	0.58	0.21	0.79	0.22	0.8	0.06	0.64
Belgium	2000-2013	0	0.45	0.45	0.33	0.33	0.72	0.72
Bulgaria	1990-2013	0.41	0.32	0.73	0.35	0.76	0.34	0.75
Croatia	1992-2013	0.66	0.22	0.88	0.22	0.88	0.29	0.95
Denmark	1990-2013	0.24	0.26	0.5	0.32	0.56	0.22	0.46
Czech R.	1993-2013	0.65	0.16	0.81	0.13	0.78	0.14	0.79
Finland	1990-2013	0.52	0.22	0.74	0.25	0.77	0.08	0.6
France	1990-2013	0.76	0.13	0.89	0.09	0.85	0.07	0.83
Greece	1990-2013	0.67	0.02	0.69	0.02	0.69	0.01	0.68
Germany	1990-2013	0.56	0.3	0.86	0.27	0.83	0.09	0.65
Hungary	1991-2013	0.66	0.13	0.79	0.15	0.81	0.16	0.82
Ireland	1990-2013	0.43	0.29	0.72	0.37	0.8	0.32	0.75
Italy	1990-2013	0.54	0.07	0.61	0.07	0.61	0.07	0.61
Latvia	1992-2013	0.48	0.15	0.63	0.15	0.63	0.21	0.69
Lithuania	1992-2013	0	0.42	0.42	0.42	0.42	0.58	0.58
Netherlands	1990-2013	0.34	0.09	0.43	0.11	0.45	0.29	0.63
Poland	**1990-2013**	**0**	0.69	0.69	**0.73**	**0.73**	0.56	0.56
Portugal	1990-2013	0.35	0.09	0.44	0.15	0.5	0.12	0.47
Romania	**1990-2013**	**0.23**	0.46	0.69	**0.5**	**0.73**	0.49	0.72
Spain	1990-2013	0.89	0.02	0.91	0.02	0.91	0.02	0.91
Sweden	1995-2013	0.33	0.27	0.6	0.23	0.56	0.04	0.37
United Kingdom	1990-2013	0	0.53	0.53	0.37	0.37	0.4	0.4

Copyright © 2014, MODEXTREME Consortium

Table 11. *Percentage of **SUGAR BEET** inter-annual yields variability (R^2) in European countries explained by (i) the technological trend; (ii) the regression model including the best combination of climatic indices and (iii) the sum of technological trend and climatic indices, at 27th, 24th and 20th ten-day period of the year.*

			27th ten-day period		*24th ten-day period*		*20th ten-day period*	
Country	**Period**	**Trend**	**Model**	**Total**	**Model**	**Total**	**Model**	**Total**
Austria	1990-2013	0.68	0.15	0.83	0.14	0.82	0.07	0.75
Belgium	2000-2013	0.73	0.08	0.81	0.07	0.8	0.05	0.78
Croatia	**1992-2013**	**0.37**	0.42	0.79	0.48	0.85	**0.5**	**0.87**
Denmark	1990-2013	0.57	0.26	0.83	0.16	0.73	0.15	0.72
Czech R.	1993-2013	0.9	0.04	0.94	0.04	0.94	0.06	0.96
France	1990-2013	0.74	0.09	0.83	0.07	0.81	0.09	0.83
Germany	1990-2013	0.81	0.08	0.89	0.1	0.91	0.09	0.9
Hungary	1990-2013	0.61	0.28	0.89	0.3	0.91	0.26	0.87
Italy	**1990-2013**	**0.42**	0.39	0.81	**0.41**	**0.83**	0.32	0.74
Netherlands	1990-2013	0.82	0.1	0.92	0.1	0.92	0.09	0.91
Romania	1990-2013	0.56	0.27	0.83	0.26	0.82	0.22	0.78
Slovakia	1993-2013	0.66	0.16	0.82	0.16	0.82	0.25	0.91
Spain	1990-2013	0.94	0	0.94	0	0.94	0	0.94
United Kingdom	1990-2013	0.62	0.1	0.72	0.09	0.71	0.1	0.72

Table 12. *Percentage of MOWN **GRASSLANDS** inter-annual yields variability (R^2) in European countries explained by (i) the technological trend; (ii) the regression model including the best combination of climatic indices and (iii) the sum of technological trend and climatic indices, at 27th, 24th and 20th ten-day period of the year.*

			27th ten-day period		*24th ten-day period*		*20th ten-day period*	
Country	**Period**	**Trend**	**Model**	**Total**	**Model**	**Total**	**Model**	**Total**
Austria	1990-2013	0.69	0.08	0.77	0.06	0.75	0.04	0.73
Belgium	2000-2013	0	0.65	0.65	0.69	0.69	0.89	0.89
Bulgaria	1990-2013	0.48	0.16	0.64	0.24	0.73	0.32	0.81
Denmark	1990-2013	0.00	0.70	0.70	0.42	0.42	0.28	0.28
France	1990-2013	0.76	0.06	0.82	0.07	0.84	0.07	0.83
Greece	1990-2013	0.65	0.08	0.73	0.02	0.67	0.04	0.69
Germany	**1999-2013**	**0**	0.74	0.74	**0.77**	**0.77**	0.74	0.74
Hungary	1996-2013	0.83	0.07	0.90	0.05	0.88	0.06	0.89
Italy	1990-2013	0.80	0.09	0.88	0.06	0.86	0.07	0.87
Lithuania	1992-2013	0.31	0.05	0.35	0.08	0.39	0.04	0.35
Romania	1990-2013	0	0.19	0.19	0.29	0.29	0.39	0.39
Slovenia	1992-2013	0	0.47	0.47	0.47	0.47	0.13	0.13
Spain	1990-2013	0.41	0.17	0.58	0.19	0.59	0.18	0.59

Copyright © 2014, MODEXTREME Consortium

2.2. Cross-validation

Figure 2 to *Figure 11* and *Table 13* show the results for the step **c)** described in *Section 1.3.2*.

In particular, results of the cross-validation applied to the combinations crop × country highlighted in bold in *Tables 3 to 13* (*Section 2.1*) are presented.

Table 13 shows (i) the agro-climatic indicators (i.e., independent variables) used within the regression models that proved to be the most accurate after the cross-validation, and (ii) the accuracy metrics derived from the comparison between official and forecasted yields. For each of the eleven crops for which the analysis was performed, good results were achieved in one or two countries. The exception was rice, for which no satisfactory results were achieved with forecasting systems based on agro-climatic indicators (see *Table 8*).

Table 13. *Accuracy indices derived from the comparison between official statistics and yields predicted applying the cross-validation procedure.*

	Crop	Country	Regression model	RRMSE	EF	CRM	R^2
Winter crops	Wheat	Spain	$ARID_{mean}$, $ARID_{cr}$, T_{maxcr}	0.24	0.80	0.00	0.82
		Slovenia	$ARID_{mean}$, $ARID_{cr}$, Fu, T_{mincr}	6.19	0.66	-0.01	0.67
	Barley	Italy	$ARID_{cr}$, Fu, T_{maxcr}, T_{mincr}	3.42	0.48	0.00	0.58
		Spain	$ARID_{cr}$, T_{maxcr}	9.84	0.84	0.01	0.85
	Rye	Spain	$ARID_{cr}$, T_{maxcr}, T_{mincr}	0.21	0.76	0.00	0.76
	Triticale	Romania	$ARID_{cr}$, Fu, T_{maxcr}	15.96	0.07	0.00	0.33
	Rapeseed	Romania	$ARID_{mean}$, T_{maxcr}	20.52	0.65	-0.03	0.66
Summer crops	Maize	Italy	$ARID_{mean}$, T_{maxcr}, T_{mincr}	4.86	0.62	0.00	0.65
		Croatia	$ARID_{mean}$, T_{maxcr}	11.36	0.68	0.00	0.71
	Sunflower	Bulgaria	$ARID_{mean}$, Fu, T_{maxcr}	12.97	0.80	0.01	0.81
		Italy	T_{maxcr}, T_{mincr}	6.87	0.43	0.00	0.45
	Potato	Romania	$ARID_{cr}$, Fu, T_{maxcr}	9.82	0.52	-0.01	0.53
		Poland	$ARID_{mean}$, $ARID_{cr}$, T_{maxcr}	8.04	0.66	0.00	0.68
	Sugar beet	Italy	$ARID_{cr}$, T_{mincr}	7.02	0.69	0.00	0.69
		Croatia	$ARID_{cr}$, Fu	10.78	0.73	0.00	0.74
	Mown Grasslands	Germany	$ARID_{mean}$, $ARID_{cr}$, T_{mincr}	4.49	0.47	0.00	0.59

Table 14 shows that the indicators $ARID_{cr}$ and T_{maxcr} are those selected more frequently as independent variables within the multiple linear regression models, whereas the indicator involved with the impact of low temperatures (i.e., T_{mincr}) rarely appears.

Most of the regression models have two or three independent variables, meaning that the forth indicator often does not lead to increase the accuracy of the forecasting system.

Copyright © 2014, MODEXTREME Consortium

The value of CRM (Table 14) was close to zero for the all the combinations crop × country, demonstrating the absence of over- or under-estimating behaviour in the forecasting systems.

On average, results achieved were satisfactory, except for triticale in Romania (*Table 14*). In this case, indeed, the regression model was able to explain 77% of inter-annual yield variability (*Table 6*). However, for this crop, the application of the model for forecasting purposes (cross-validation) revealed a scarce robustness of the regression model: the differences between official and forecasted yields were rather accentuated, especially in 2003 and 2009 (*Figure 5*), leading to R^2 and EF values of 0.33 and 0.07, respectively. A possible explanation is related with the length of the available series of official yields (starting from 2002).

The best performances were achieved for wheat, barley and rye in Spain, with 82%, 85% and 76% of yield variability captured by the forecasting system, and with EF ranging from 0.76 to 0.8. *Figure 2a*, *Figure 3b*, *Figure 4* show that the trend of yields during the time window is well reproduce without marked differences between official and forecasted yields. Indeed, Spain is mainly characterized by a Mediterranean climate and winter crop production is mostly driven by rainfall volumes and distribution during the growing season.

Good results were also achieved for sunflower in Bulgaria (*Figure 7a*) and sugar beet in Croatia (*Figure 10a*) with R^2 values of 0.81 and 0.74, respectively. However a great part of yield variability was explained by the introduction of technological innovations, especially in Bulgaria, where the regression model explained only 20% of the year-to-year yield fluctuations.

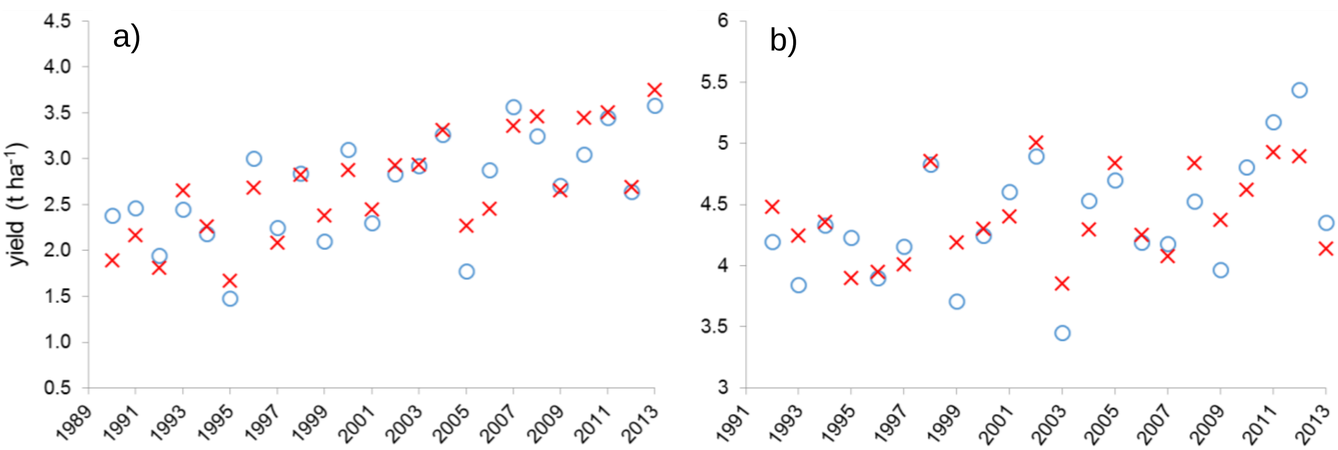

***Figure 2**. Comparison between measured (empty blues circles) and predicted yields (red crosses) of **WHEAT** in a) Spain and b) Slovenia*

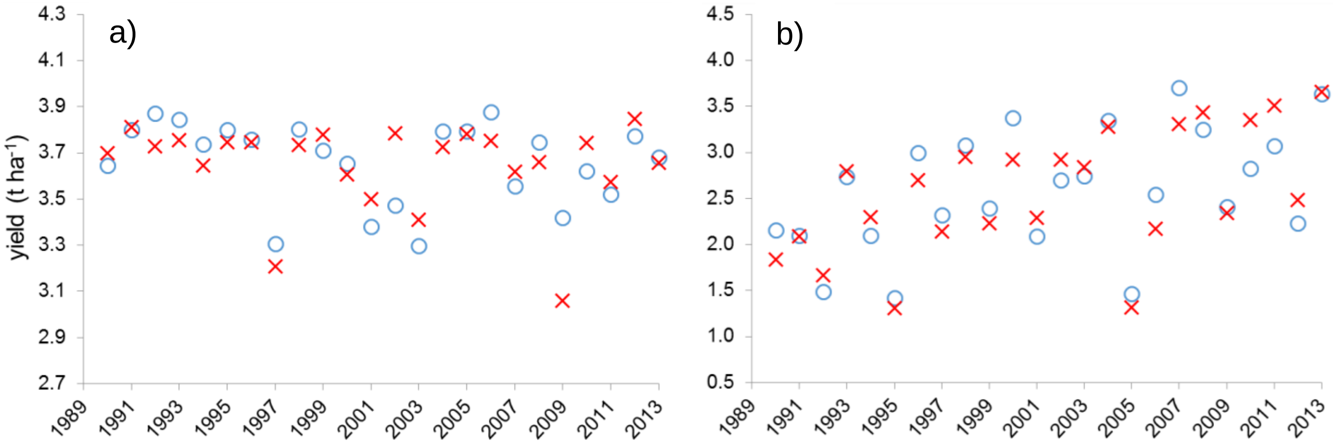

Figure 3. *Comparison between measured (empty blues circles) and predicted yields (red crosses) of* ***BARLEY*** *in a) Italy and b) Spain*

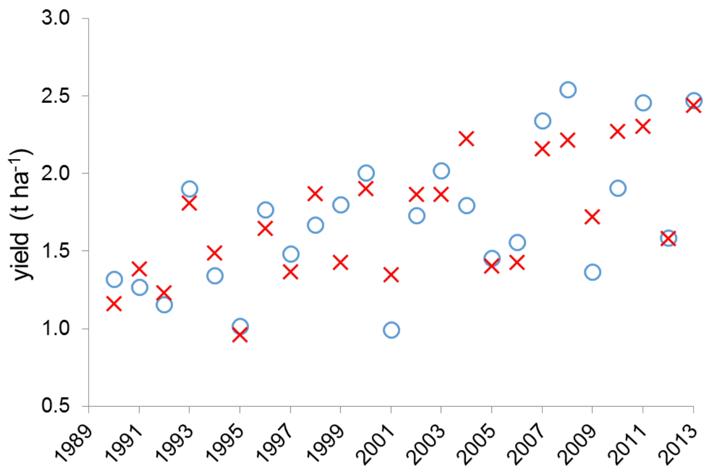

Figure 4. *Comparison between measured (empty blues circles) and predicted yields (red crosses) of* ***RYE*** *in Spain*

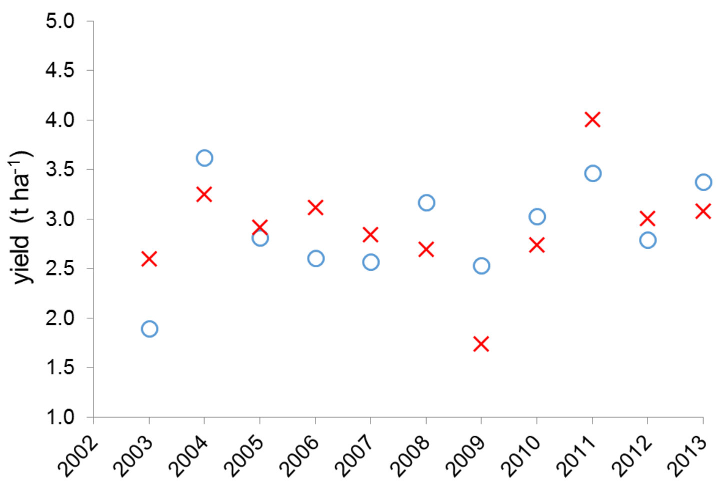

Figure 5. *Comparison between measured (empty blues circles) and predicted yields (red crosses) of* ***TRITI-CALE*** *in Romania*

Copyright © 2014, MODEXTREME Consortium

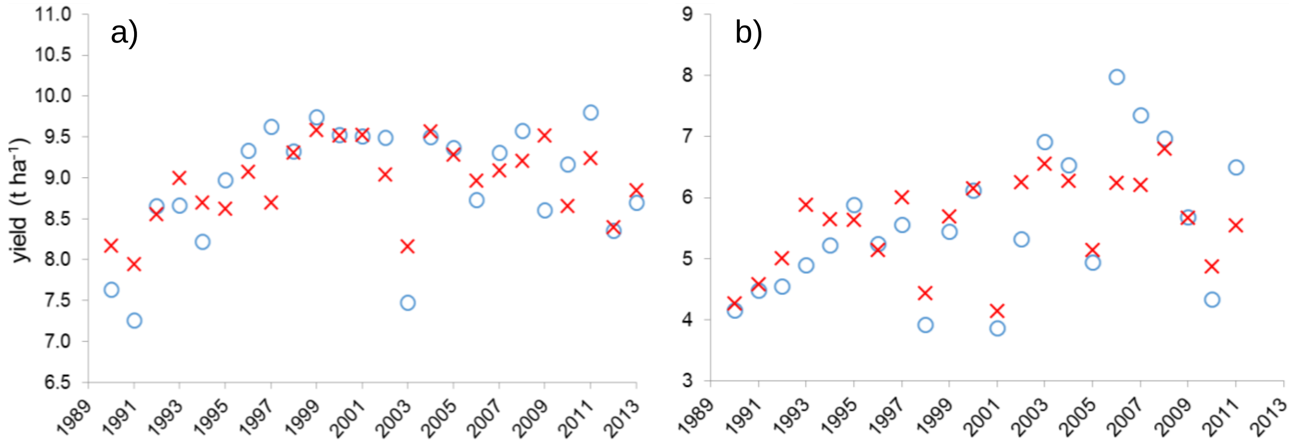

Figure 6. *Comparison between measured (empty blues circles) and predicted yields (red crosses) of* ***MAIZE*** *in a) Italy and b) Croatia*

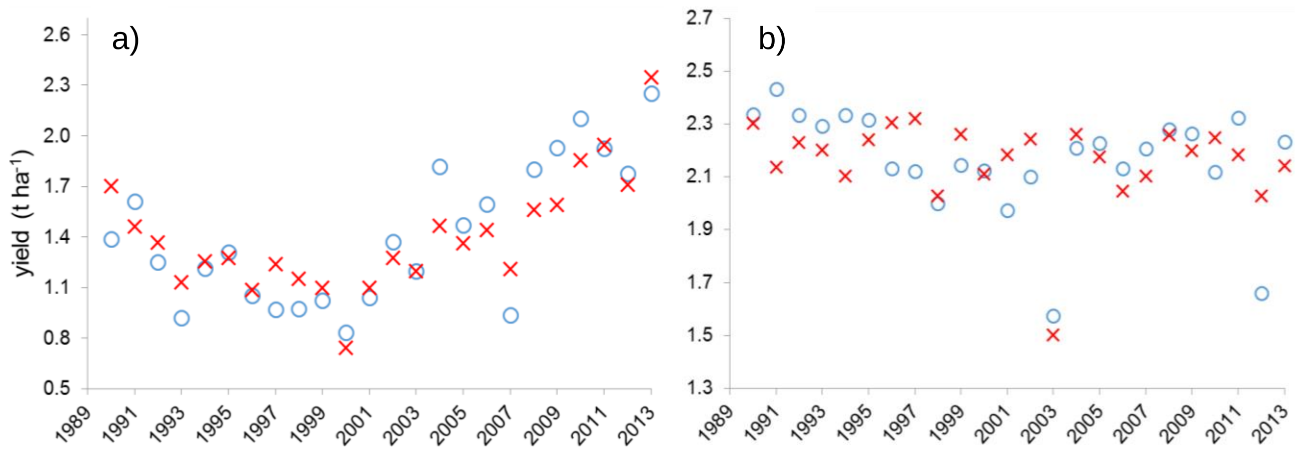

Figure 7. *Comparison between measured (empty blues circles) and predicted yields (red crosses) of* ***SUN-FLOWER*** *in a) Bulgaria and b) Italy*

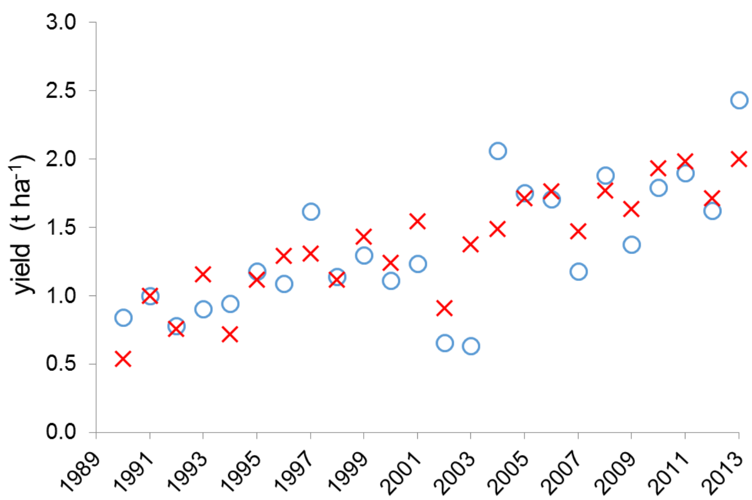

Figure 8. *Comparison between measured (empty blues circles) and predicted yields (red crosses) of* ***RAPE-SEED*** *in Romania*

Copyright © 2014, MODEXTREME Consortium

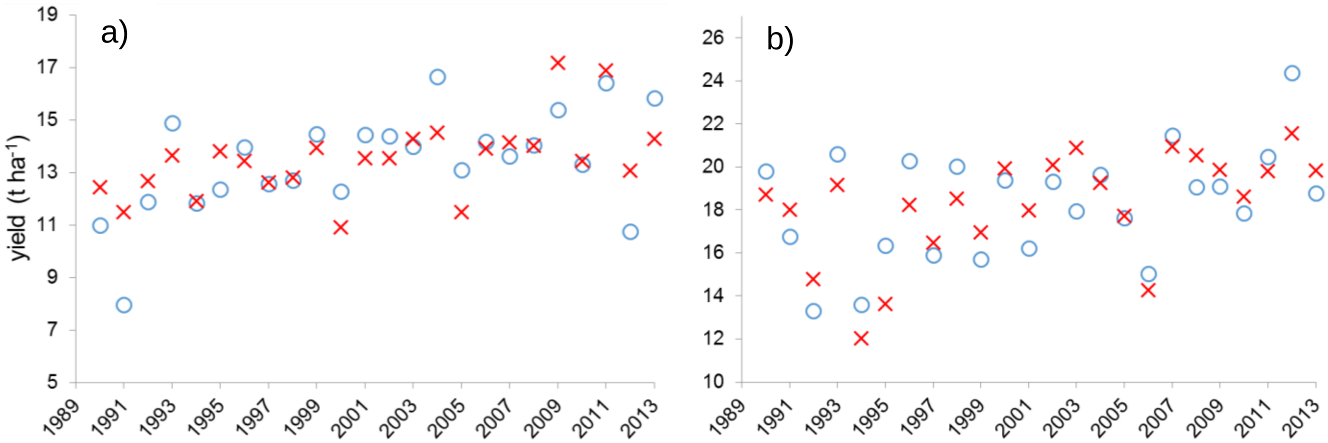

Figure 9. *Comparison between measured (empty blues circles) and predicted yields (red crosses) of **POTATO** in a) Romania and b) Poland*

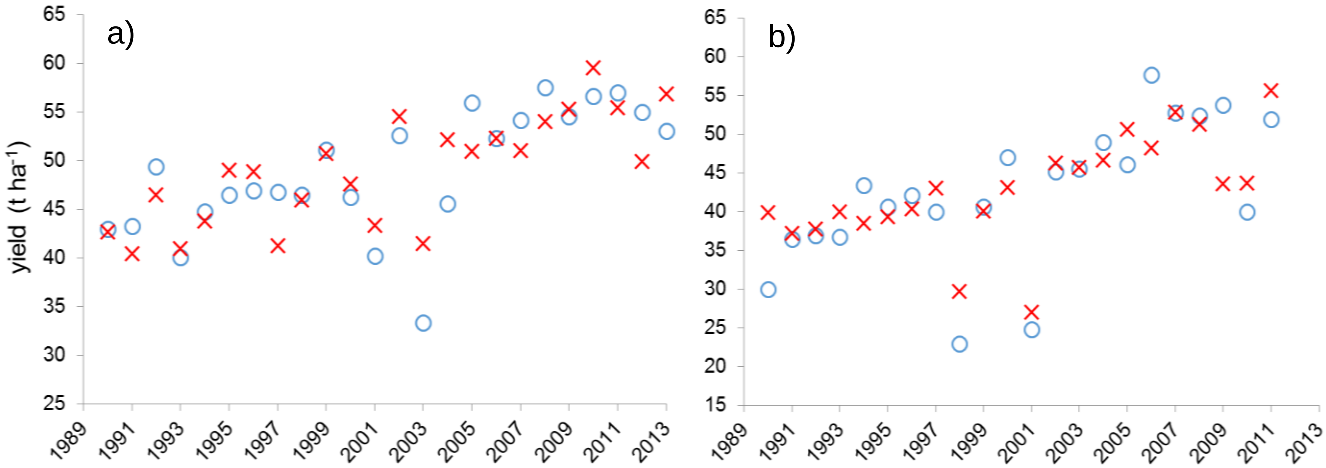

Figure 10. *Comparison between measured (empty blues circles) and predicted yields (red crosses) of **SUGAR BEET** in a) Italy and b) Croatia*

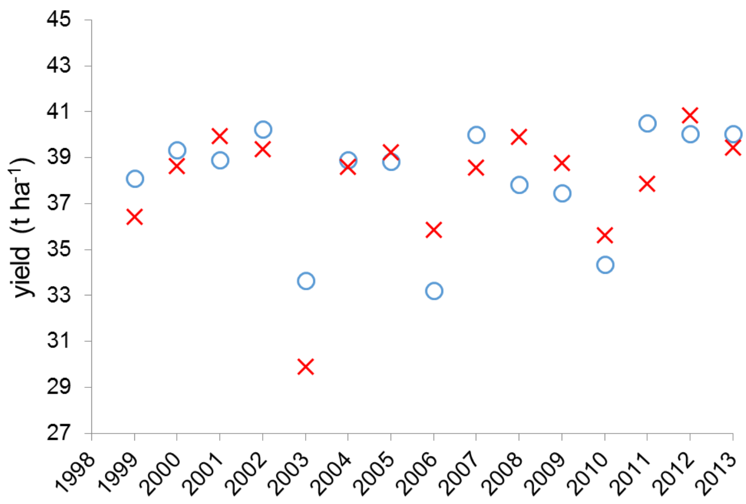

Figure 11. *Comparison between measured (empty blues circles) and predicted yields (red crosses) of **GRASS-LANDS** in Germany*

Copyright © 2014, MODEXTREME Consortium

In conclusion, the applied methodology led to satisfactory forecasting performance in countries where crop production is mainly driven by the trend of a specific meteorological variable during the season; in this case extreme events (e.g., drought, temperatures higher or lower than critical thresholds). Moreover, with a focus on extreme weather events, this approach can potentially provide a solution for being integrated with dynamic models to assess crop responses to the occurrence of extreme events within climate change scenarios.

Moreover, the applied method is characterized by limitations related to the aggregation procedure of the agro-climatic indices at national level which leads to a substantial information loss considering that in some cases, the spatial resolution at which extreme events occur is too high for being properly captured by analyses performed at national level. An additional limitation in the aggregation procedure is caused by the uncertainty related to crop distribution, which was assumed constant for the entire time window.

Copyright © 2014, MODEXTREME Consortium

References

Balaghi, R., Jlibene, M., Tychon, B., Eerens, H., 2012. Agrometeorological Cereal Yield Forecasting in Morocco. INRA, Rabat, Maroc, 149 p.

Bannayan, M., Crout, N.M.J., 1999. A stochastic modelling approach for real-time forecasting of winter wheat yield. Field Crops Research 62, 85-95.

Bouman, B.A.M., Van Diepen, C.A., Vossen, P., Van Der Val, T., 1997. Simulation and systems analysis tools for crop yield forecasting, in: Teng et al. (Eds), Applications of Systems Approaches at the Farm and Regional Levels 1 325-340.

Bouman, B.A.M., 1995. Crop modelling and remote sensing for yield prediction. Netherlands Journal of Agricultural Science 43, 143-161.

Confalonieri, R., Bellocchi, G., Donatelli, M., 2010. A software component to compute agro-meteorological indicators. Environmental Modelling & Software 25, 1485-1486.

Fu, B.P., 1981. On the calculation of the evaporation from land surface (in Chinese). Chinese Journal of Atmospheric Sciences 5, 23-31.

Haylock, M. R., Hofstra, N., Klein Tank, A. M. G., Klok, E. J., Jones, P. D., New, M., 2008. A European daily high-resolution gridded data set of surface temperature and precipitation for 1950–2006, Journal of Geophysical Research, 113, D20119.

Jorgensen, S.E., Kamp-Nielsen, L., Christensen, T., Windolf-Nielsen, J., Westergaard, B., 1986. Validation of prognosis based upon a eutrophication model. Ecological. Modelling 35, 165-182.

Loague, K., Green, R.E., 1991. Statistical and graphical methods for evaluating solute transport models: overview and application. Journal of Contaminant Hydrology 7, 51-73.

Monfreda, C., Ramankutty, N., Foley, J.A., 2008. Farming the planet: 2. Geographic distribution of crop areas, yields, physiological types, and net primary production in the year 2000. Global Biogeochemical Cycles 22, GB1022.

Narasimhan, B., Srinivasan, R., 2005. Development and evaluation of soil moisture deficit index and evapotranspiration deficit index for agricultural drought monitoring. Agricultural and Forest Meteorology 133, 69-88.

Nash, J.E., Sutcliffe, J.V., 1970. River flow forecasting through conceptual models. Part I – a discussion of principles. Journal of Hydrology 10, 282-290.

Rivington, M., Matthews, K., Miller, D., Bellocchi, G., Russell, G., 2013. Climate change impacts and adaptation scope for agriculture indicated by agro-meteorological metrics. Agricultural Systems 114, 15-31.

Supit, I., 1997. Predicting national wheat yields using a crop simulation and trend models. Agricultural and Forest Meteorology 88, 199-214.

Trnka, M., Olesen, J.E., Kersebaum, K.C., Skjelvåg, A.O., Eitzinger, J., Seguin, B., Peltonen-Sainio, P., Orlandini, S., Dubrovsky, M., Hlavinka, P., Balek, J., Eckersten, H., Cloppet, E., Calanca, P., Rötter, R., Gobin, A., Vucetic, V., Nejedlik, P., Kumar, S., Lalic, B., Mestre, A., Rossi, F., Alexandrov, V., Kozyra, J., Schaap, B., Zalud, Z., 2011. Agroclimatic conditions in Europe under climate change. Global Change Biology 17, 2298–2318.

Copyright © 2014, MODEXTREME Consortium

Van Keulen, H., Wolf, J., 1986. Modelling of agricultural production: weather soils and crops. Simulation Monographs, Pudoc, Wageningen, The Netherlands, pp. 479.

Vossen, P., Rijks, D.A., 1995. Early crop yield assessment of the E.U. countries. The system implemented by the Joint Research Centre. Publication EUR 16318 EN of the Office for Official Publications of the E.U. Luxembourg.

Woli, P., Jones, J.W., Ingram, K.T., Fraisse, C.W., 2012. Agricultural Reference Index for Drought (ARID). Agronomy Journal 104, 287.

Zhang, L., Hickel, K., Dawes, W.R., Chiew, F.H.S., Western, A.W., Briggs, P.R., 2004. A rational function approach for estimating mean annual evapotranspiration: Estimating mean anual evapotranspiration. Water Resources Research 40, W02502.

Copyright © 2014, MODEXTREME Consortium