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Crop planting date matters: Estimation methods and effect on future yields

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ABSTRACT

Productivity of arable lands highly depends on the management techniques and their timing. Climate change urges the need for adaptive management tools, such as methods for optimization of planting date (PD). In existing crop models PD is usually specified by the user as a fixed date or through a set of rules which depend on diverse environmental conditions. However, validated rules of PD calculation are rare in the existing literature. In this study we strived to develop methods that could reliably estimate the PDs based on soil temperature and soil moisture, as well as to provide tool for PD projections under climate change. PD data from 294 agricultural enterprises in Hungary during the period from 2001 to 2010 were used to validate the PD methods. Effect of climate change on the timing of PD was evaluated using an ensemble of 10 climate change projections. Meteorological and soil data were obtained from the Open Database for Climate Change Related Impact Studies in Central Europe (FORESEE) and Soil and Terrain (SOTER) databases. The 4M crop model was used for crop yield simulations. Relative to the present day conditions, our analysis predicts a shift to earlier PDs for maize (approx. 12 days) and later PD for winter wheat (approx. 17 days) for the 2071–2100 period. The results indicated that maize PDs should be changed according to the earlier start of the growing season in spring. In contrast, currently used PDs should be preserved for winter wheat to avoid climate change related yield loss. Our analyses showed that the proposed PD estimation methods performed better than other eight tested methods. The advantage of our novel rules is that they could be applied for other crop models, as well.

1. Introduction

Food security is one of the most important global challanges with respect to the continuously growing population (Godfray et al., 2010; Foley et al., 2011). At global scale, arable land covers ~12% of the terrestrial land surface (Drewniak et al., 2013). The productivity of agricultural lands is greatly affected by applied management practices (e.g. planting, irrigation, fertilizing, tilling, harvesting, weed management) and their timing (Twine et al., 2004). Sustainable agricultural production is essentially required to provide food and fibre for the world's population, and to feed the livestock, which could be potentially supported by appropriate, adaptive management practices (Godfray et al., 2010; Tilman et al., 2011).

Agro-ecological models are often used in climate change and food security related studies (Rosenzweig and Parry, 1994; Parry et al., 2004; Ewert et al., 2005; Bondeau et al., 2007; Fodor and Pásztor, 2010; Bassu et al., 2014) to predict the future crop production. The models typically use climate, soil, crop ecophysiological parameters and management information to provide estimates of future yields as well as of the effect of diverse management practices (Mo and Beven, 2004; Baigorria et al., 2008; Ewert et al., 2002; Ma et al., 2012). Specific "*in silico* agronomic trials", where modellers keep specific conditions unchanged (e.g. management, crop genotypes) and only test effects of changes in some model parameters were found supportive to identifying variables which are worth to be addressed by management decisions (Alexandrov et al., 2002;

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Alexandrov and Eitzinger 2005; Olesen et al., 2011). This approach is particularly useful as future crop production will be modulated by changes in a multitude of factors, such as temperature, precipitation patterns, atmospheric CO_2, extreme events, pests, change of crop cultivars, irrigation practices etc., which are difficult to capture and evaluate by farmers (Gornall et al., 2010; Olesen et al., 2011). Such complex issues can be addressed by models effectively, and responses of production indicators to selected treatments can be tested. Still, field experiments are inevitably needed to parameterize the models and justify the relevance of modelling outputs.

Planting date (PD) is a fundamental management information, which is typically required by crop models (Waha et al., 2012). Timing of sowing has a considerable effect on the yields (Kucharik, 2008) due to the variability of weather (timing and amount of wet and dry periods, temperature variability) that strongly interacts with crop phenophases (Drewniak et al., 2013; Tsimba et al., 2013; Wolf et al., 2015).

Climate change has already been found to modify plant phenology mainly due to the extension of the growing season in many areas (Penuelas and Filella, 2001; Estrella et al., 2007; Lobell and Field, 2007; Olesen et al., 2011). Shifts in precipitation patterns (e.g. the expected decrease in summer precipitation in Central Europe; Pongrácz et al., 2011; Dobor et al., 2015) together with earlier growing season start require reconsideration of existing PDs in order to avoid drought induced yield loss. In order to create adaptive agro-ecological simulations, realistic estimations of human management practices are needed, including planting practice and its potential changes in the future.

Three PD estimation methods are used in crop modelling for different purposes (Waha et al., 2012). The first method uses predefined, constant PDs based on observations, typically representing average planting time for some period (De Noblet-Ducoudré et al., 2004; Fodor and Pásztor, 2010; Cammarano et al., 2012; Drewniak et al., 2013; Elliott et al., 2015). Some studies optimized the PDs in order to maximize the yield (Stehfest et al., 2007; Waongo et al., 2015; Wolf et al., 2015). The third approach uses climate data to estimate the optimal conditions for a given crop for planting (Jones et al., 2003; Bondeau et al., 2007; Waha et al., 2012; Holzworth et al., 2014), and can be particularly useful in climate change impact studies. The present study mainly focuses on the first and the third methods.

In addition to the fixed PD option, the majority of state-of-the-art crop models allow to define the so-called rule-based PDs (Moore et al., 2014). For example, the CropSyst model (version 4.12.10) determines the PD by air temperature and the actual soil water content (Stöckle and Nelson, 1996; Stöckle et al., 2003). The STICS model uses soil moisture and precipitation thresholds to determine the PD (version 5.0; Brisson et al., 2003). In the DSSAT model soil water content, management depth for water and soil temperature thresholds need to be set to estimate PD within a given sowing window (version 4.6, Jones et al., 2003; Hoogenboom et al., 2015). The APSIM model provides opportunity for user-defined sowing rules based on any internally calculated model variable (version 7.7, Keating et al., 2003; Holzworth et al., 2014), which provides more flexibility than the other models.

It is notable that in these state-of-the-art models the modeller has a large degree of freedom in rule definition, and no region-specific, ready-to-use (default for a given region and/or crop) rules are available. This means that the modeller might (unintentionally) choose rules that provide unrealistic PDs for a given region.

Most of the studies in the literature estimate PDs based on air temperature only (De Noblet-Ducoudré et al., 2004; Drewniak et al., 2013; Waha et al., 2012; Deryng et al., 2011) but fixed-day have been used as well (De Noblet-Ducoudré et al., 2004; Drewniak et al., 2013; Elliott et al., 2015). Another approach is to use the so-called crop calendars that were constructed based on long term observations providing a fix PD for a given location (MIRCA2000, Portmann et al., 2010; Crop Calendar, Sacks et al., 2010). A few studies consider soil moisture and precipitation (Leenhardt and Lemaire, 2002; Maton et al., 2007; Trnka et al., 2011).

Available, climate dependent methods (e.g. Waha et al., 2012) perform quite well on global or continental scale, but their applicability in smaller scales is questionable (Sacks et al., 2010; Waha et al., 2012; Drewniak et al., 2013). Consequently, a lack of region-specific and ready-to-use, validated rules hampers the application of crop models. In this study, we exploited of a unique PD database to test the applicability of the methods. Application of this observation-based dataset ensures the realism in the PD modelling methods.

In many crop land areas (including Hungary, which is investigated in this study), PDs depend on meteorological conditions of the given year. Farmers start sowing when they find the conditions suitable for germination. In the Hungarian agricultural sector, soil temperature is measured at 10–12 cm depth, where the temperature required for different cultivars of maize is 8–12 °C (Vágvölgyi and Varga, 2011). Soil moisture has been also used in Central Europe to define the PDs (Eitzinger et al., 2012); specifically, low moisture holds seed germination, while too high moisture may prevent the farmers to use the sowing machinery in the field.

Weather forecasts are also used to support the decisions on PDs definition (Das et al., 2012). If soil conditions are favourable, farmers might use a weather forecast to determine the optimal time for the pre-emergent weed control. The chance of rain in the forthcoming days might trigger sowing especially if the soil is dry.

Availability of the machinery needed for sowing also affects the PD. In practice, the tractors used for sowing might be available for the farmer within a given time frame which can clearly overwrite other considerations.

The mathematical representation of the farmers' decisions that affect the PD is challenging because of a large portion of subjective factors included in such decisions. In our study we focused only on those factors that can be quantitatively described in order to construct a PD estimation method that can support crop models, and can be used to evaluate the effect of climate change on PD timing, as well.

The main aims of this study are: 1) evaluate the performance of available, literature-based PD estimation methods in Hungary; 2) develop new, rule-based methods that improve the PD calculations for maize and winter wheat; 3) identify PD estimation methods that best match the observed PDs and can be used for PD determination in crop models; 4) estimate the impact of climate change on the calculated PDs and subsequently on crop yields; 5) develop recommendations for sowing date planning under changing climate.

The paper focuses on maize and winter wheat due to dominance of these crops in Central Europe. This study strives to support crop yield modelling in Europe by regional calibration of crop models, focusing particularly on PD assessment, and thus improve the options for planning under transient environmental conditions.

2. Materials and methods

2.1. Climate data and target area

Weather dependent PDs were simulated based on the FORESEE database (Open Database for Climate Change Related Impact Studies in Central Europe; Dobor et al., 2015). FORESEE was developed to support the research of, and adaptation to climate change in Central and Eastern Europe. FORESEE contains the seamless combination of gridded daily observation-based data (1951–2013) built on the E-OBS (Haylock et al., 2008) and CRU TS 1.2 datasets (Mitchell et al., 2004), and a collection of climate projections (2014–2100).

Table 1
List of the coupled Regional Climate Models (RCM) and Global Circulation Models (GCM) used in the FORESEE database.

Model ID	Model name (RCM-GCM)	Developing institute
1	ALADIN-ARPEGE	National Centre for Meteorological Research (CNRM)
2	CLM-HadCM3Q0	Swiss Federal Institute of Technology Zürich (ETHZ)
3	HadRM3Q0-HadCM3Q0	Hadley Centre for Climate Prediction and Research (HC)
4	HIRHAM5-ARPEGE	Danish Meteorological Institute (DMI)
5	HIRHAM5-ECHAM5	Danish Meteorological Institute (DMI)
6	RACMO2-ECHAM5	Royal Netherlands Meteorological Institute (KNMI)
7	RCA-ECHAM5	Sweden's Meteorological and Hydrological Institute (SMHI)
8	RCA-HadCM3Q0	Sweden's Meteorological and Hydrological Institute (SMHI)
9	RegCM3-ECHAM5	Abdus Salam International Centre for Theoretical Physics (ICTP)
10	REMO-ECHAM5	Max-Planck-Institute for Meteorology (MPI)

The future climate is represented by bias-corrected meteorological data from ten regional climate models (RCMs), driven by the A1B emission scenario (Table 1) based on raw climate data disseminated within the framework of the ENSEMBLES FP6 project (Van der Linden and Mitchell, 2009). The ten models included in the database were selected based on temporal coverage, completeness and other criteria (for details see Dobor et al., 2015) of the 31 RCM output available on the ENSEMBLES website.

This study focuses on Hungary. The used climatological data from the FORESEE database have spatial resolution of $1/6 \times 1/6^{\circ}$ (see http://nimbus.elte.hu/FORESEE/map_query/index.html). PDs were calculated for each grid cell for the period 1951–2100. Daily FORESEE weather data were also used as inputs for the crop model. Grid cells in elevations where the investigated crops occur only marginally (average elevation > 300 m a.s.l.) were excluded using the SRTM Digital Elevation Model (Jarvis et al., 2008).

Due to the lack of usable data on soil water content, we calculated it using the hydrological sub-model of the applied crop model (tipping bucket method; Ritchie, 1998).

2.2. Planting date experiment data and planting date database

Effect of PD on crop yield was experimentally studied in Hungary, at the Centre for Agricultural Research in a long-term field experiment (Martonvásár: N47°17′ E18°48′, 131 m a.s.l.) launched in 2001. Four different PDs (10 April, 25 April, 5 May, 15 May) were used during the 2001–2013 time period at different parcels with maize, and the associated yields were recorded. Based on the 13 years of observation the timing of sowing caused about 2 t ha^{-1} (~25%) mean variability in the annual yield. Similar results were presented for winter wheat by Árendás et al. (2003). The experimental data was used to validate 4M for climate dependent PD simulations.

Observed, actual PD data were collected from 294 agricultural enterprises in Hungary for the 2001–2010 period, for maize and winter wheat (Fig. 1). Only approximate geographical locations are given, as the enterprises remained anonymous in the database. The database was used to validate the tested PD estimation methods. Using such long dataset of observed PDs is not common in the literature, which adds value to this study.

2.3. Crop model

The 4M crop model was used to estimate soil specific variables, and the effect of PD on crop yields. 4M model was developed on the basis of the CERES model (Ritchie et al., 1998). It is a daily-step, deterministic model that simulates the water and nutrient balance of the soil, the soil-plant interactions as well as the plant development and growth (Fodor and Kovács, 2003; Fodor et al., 2014). 4M determines the development rate based on the daily thermal time using base temperature as a crop specific parameter. The model calculates the mass production of the crop using a radiation-mass conversion equation. Radiation use efficiency and the leaf area index are the key parameter and variable in the equation, which includes the air temperature, water and nitrogen stress factors, as well as a factor expressing the effect of air CO_2 concentration on biomass formulation. The produced mass is distributed among the main parts (root, stem, leaf, grain) of the plant according to user-defined ratios that might change dynamically in different phenological stages. Root, stem and leaf area expansions are functions of the mass allocated to the corresponding part of the plant. Water and nitrogen stress factors are calculated based on the ratio of the crop's demand and the supply available in the root zone. Leaf senescence is also calculated based on thermal time determined leaf age, but this process could be accelerated by extreme environmental conditions. Soil water balance is calculated using the tipping bucket method including procedures for estimating evaporation, surface runoff, upward flow through the capillaries and plant water uptake (transpiration) (Ritchie, 1998).

The 4M model was used in a number of previous studies focusing on soil and weather influence on crop yields (Máthé-Gáspár et al., 2005) and on impacts of climate change on crop production in Hungary (Fodor and Pásztor, 2010; Fodor et al., 2014).

2.4. Parameterization of 4M

Soil specific model input data were retrieved from the georeferenced database of the Centre for Agricultural Research, Hungarian Academy of Sciences (MTA ATK) Institute for Soil Sciences and Agricultural Chemistry (SOTER database; Várallyay et al., 1994). The soil of each grid cell was represented by the parameter set (bulk density, organic matter content, field capacity, saturated hydraulic conductivity, etc.) of the dominating soil type of the cell according to their textural characteristics. For the simulations, the following agro-management settings were used. PDs were estimated with the sowing rules defined in Section 2.5. based on meteorological data and soil parameters. Plant density was 7 and 500 plants m^{-2} for maize and wheat, respectively. Harvest was timed after physiological maturity. Nitrogen fertilizer was applied 10 days before planting (170 kg ha^{-1}) for maize, and 14 days before, and 146 and 190 days after the planting for wheat in each year (30, 100, 20 kg ha^{-1}, respectively).

The plant specific input parameters were calibrated using the method proposed by Klein et al. (2012). County level (NUT–S 3 level) harvest statistics of wheat and maize from the period 1981–2000 published by the Hungarian Central Statistical Office (http://www.ksh.hu/?lang=en) were used for parameter optimization. The approximate values of the plant specific parameters (phenological characteristics and stages, maximum root depth, radiation use efficiency, specific leaf area, specific N content, etc.) were based on Stöckle and Nelson (1996). Then, the most important parameters (Table 2) were fine-tuned so as the root mean square error of the simulated yields was minimized.

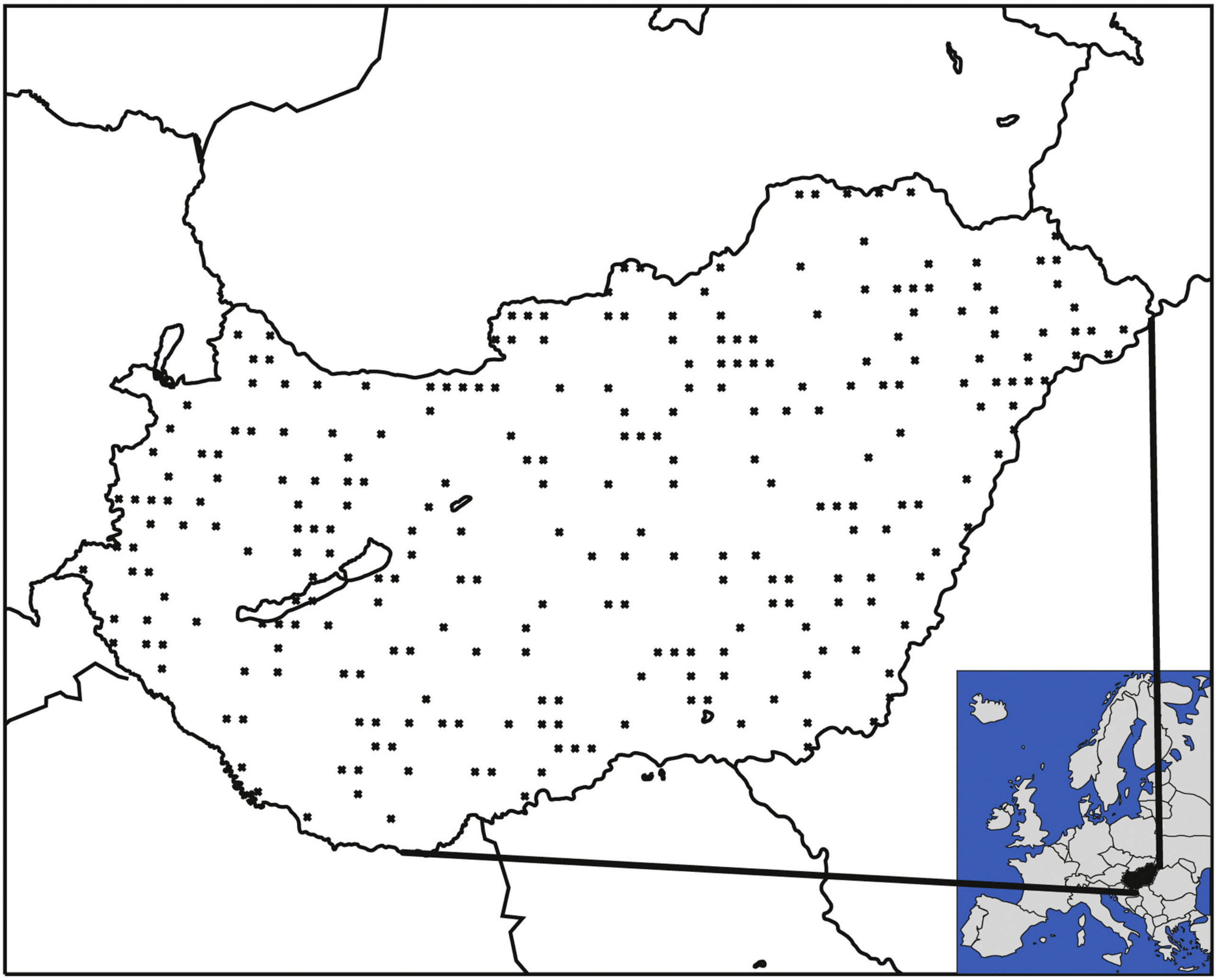

Fig. 1. Map of Hungary and the approximate geographical location of the 294 enterprises that reported PD information to the study. Inset shows the map of Europe with the location of Hungary.

Table 2
The most important, calibrated plant parameters of the 4M model. GDD: growing degree-day.

Parameter	Crop	
	Maize	Winter wheat
Base temperature (°C)	8	0
GDD from emergence to flowering (°Cd)	720	950
Radiation use efficiency (gMJ^{-1})	3.85	2.60
Specific leaf area (m^2kg^{-1})	20	25
Maximum root depth (m)	1.7	1.3

Model calibration was performed using fixed PDs (20 April for maize and 15 October for winter wheat; day of year (doy) 110 and 288 in regular years, respectively). These fixed dates were set by expert knowledge at the time of model calibration. 4M was evaluated against observations in previous studies (Fodor, 2012; Fodor et al., 2014), however climate-dependent PDs were not used previously with 4M.

2.5. Planting day calculation

In Hungary maize and winter wheat are sown in the first and the second half-year, respectively. The search for the PDs was confined to these half-years depending on the crop type. We used eight methods described in the literature and twelve methods proposed in this study (Tables 3 and 4).

Table 3
Collection of methods (based on literature review) to calculate the PDs for maize and winter wheat. *doy*: day of year. *aT*: average daily air temperature at 2 m; *aTc*: average air temperature of the coldest month.

Maize		
ID	criteria	reference
M-1	*doy* when $aT > 8$ °C	Birch et al. (1998)
M-2	*doy* when $aT > 10$ °C	Coffman (1923); Pan et al. (1999)
M-3	*doy* when $aT > 12.8$ °C	Kiniry et al. (1995)
M-4	*doy* when $aT > 12.1$ °C	Sacks et al. (2010)
M-5	*doy* when $aT > 14$ °C	Waha et al. (2012)
M-6	*doy* when $aT > 10$ °C for 7 days	Lokupitiya et al. (2009)
Winter wheat		
ID	criteria	reference
W-1	*doy* when $aT < 12$ °C	Waha et al. (2012)
W-2	$doy = 3.06 * aTc + 281$	Sacks et al. (2010)

The simple methods from the literature use only daily air temperature to estimate the PD (Table 3). As soil conditions represented by moisture content can be used to constrain the timing (Cooper et al., 1997; Eitzinger et al., 2012; Rotz and Harrigan, 2005), this parameter was introduced in some of the novel methods (Table 4).

Table 4
Novel methods to calculate the PDs for maize and winter wheat. *doy*: the day of the year. *aT*: average daily air temperature at 2 m; *3dayTprec*: total precipitation amount of the last 3 days; *NWC*: normalized water content of the topsoil; *soilT*: temperature of the topsoil.

Maize	
ID	rule(s)
M-I	*doy* when *aT* > 12 °C for 7 days
M-II	*doy* when *aT* > 12 °C for 7 days and *3dayTprec* < 2 mm
M-III	*doy* when *aT* > 12 °C for 7 days and 20% < *NWC* < 80%
M-IV	*doy* when *aT* > 12 °C for 7 days and 20% < *NWC* < 80% and *soilT* > 10 °C for 10 days
M-V	*doy* when *aT* > 12 °C for 5 days and 20% < *NWC* < 80% and *soilT* > 10 °C for 5 days
M-VI	*doy* when *aT* > 10 °C for 7 days and 20% < *NWC* < 80% and *soilT* > 10 °C for 5 days
M-VII	*doy* when *aT* > 10 °C for 7 days and 20% < *NWC* < 80% and *soilT* > 10 °C for 7 days
M-VIII	*doy* when *aT* > 11 °C for 5 days and 20% < *NWC* < 80% and *soilT* > 11 °C for 5 days

Winter wheat	
ID	rule(s)
W-I	*doy* when *aT* < 12 °C for 7 days
W-II	*doy* when *aT* < 12 °C for 7 days and 20% < *NWC* < 80%
W-III	*doy* when *aT* < 13 °C for 7 days and 20% < *NWC* < 80%
W-IV	*doy* when *aT* < 14 °C for 7 days and 20% < *NWC* < 80%

Additionally, too dry soil conditions have to be avoided as germination can be inhibited during dry periods. In the M-II method restriction on soil wetness is involved indirectly, i.e. total amount of precipitation is limited to 2 mm for 3 days prior to sowing. In the M-III – M-VIII and W-II – W-III methods, information on soil conditions is used directly. These methods require the normalized water content (NWC) of the topsoil to be in the 20–80% range. The NWC is defined as:

$$NWC = 100 \times \frac{\Theta - \Theta_r}{\Theta_S - \Theta_r}, \quad (1)$$

where θ is the volumetric water content, while θ_r and θ_S are the residual and the saturated water content of the soil, respectively. The advantage of the NWC over the simple volumetric water content is that it implicitly includes information about the soil hydro-physical characteristics.

As soil temperature is widely used in the agronomy sector for planting related decisions, additional topsoil temperature (soilT) limit was set in the M-IV – M-VIII methods based on Sárvári and Futó (2001) and Nagy (2007) (Table 4).

We also tested the option to include the weather forecast consideration of farmers described in the Introduction. However, this additional criteria had negligible effect on the PDs (see Supplementary material S1), thus they were not included in our rules. This decision is justified by the fact that modellers need simple planting date rules, which use minimal input data.

Methods that take into account soil conditions to determine the PD use information on soil status, which was estimated by a preceding 4M simulation with unrealistically late PDs.

One of our primary aims was to compare the simulated crop yields in the future using fixed day and weather dependent PD estimation methods. In order to create comparable estimations with fixed day and weather dependent PD methods the yields in the reference period (1990–2013) should match. It is only reasonable if the mean PDs estimated by the two methods are approximately the same (i.e. their difference is the smallest). To allow selection of method that best matches the fixed date used by 4M by default, we created a set of fine-tuned methods. The resulting methods differ only slightly but allow variability in the estimated dates (M-V, M-VI, M-VII, M-VIII, W-III, W-IV). Selection of the most appropriate, fine-tuned method was done based on their 63-years mean estimation. The preferred fine-tuned method gave PD that approximated the static dates used by 4M (20 April for maize and 15 October for winter wheat) for Hungary.

For each PD estimation method, annual spatial averages and their standard deviations over the target area were determined for the period 1951–2013 and 2014–2100. Although PDs were calculated for each grid cell within Hungary, for validation only results from the grid cells of the observation database were used.

Future PDs (2014–2100) were calculated using selected methods based on the 10 different climate models provided by FORESEE (Table 1). This multi-model approach enables us to assess the uncertainty in PD estimations related to future climate development.

2.6. Performance of the planting date estimation methods

We compared basic statistics from the observed and simulated PDs (mean, median, standard deviation, minimum, maximum, 5th and 95th percentile). We also used two-sided Kolmogorov-Smirnov statistic to compare the distribution of the observations and the estimations. The Kolmogorov-Smirnov statistic provides the maximum distance between the cumulative distributions of the observation and simulation dataset, and can be used to evaluate the similarity or dissimilarity of two datasets.

A simple criterion was also constructed to support the acceptance or rejection of a PD estimation method (note that acceptance does not necessarily mean that the method is the optimal one). A PD method was accepted if 90% of its calculated dates fell in-between the limits that were defined based on the observations. The limits defining the real sowing periods were the minimum and maximum of the observed date of the planting for a given crop type during the 2001–2010 period (when observations are available). These limits were 3 April (doy 93) and 14 May (doy 134) for maize, and 18 September (doy 261) and 11 November (doy 315) for winter wheat.

According to the criteria for the 63-years long time period of 1951–2013 an acceptable method was required to miss the targeted time-window in 6 times at maximum, while only 1 outlier was allowed for the accepted method during the 2001–2010 time period.

PDs were calculated for the 1951–2013, and also for the 2001–2010 period, in the observation points (Fig. 1).

For one crop type two optimal PD estimation methods were selected based on two different criteria.

In the first criterion, the optimal PD estimation method was the one, which could best reproduce the observed dates. PD estimations provided by the accepted methods were used to construct a simple metric to select the best method. The basic statistics calculated from the estimated and observed dates were used to construct a two dimensional (2D) decision space where the distance of the point

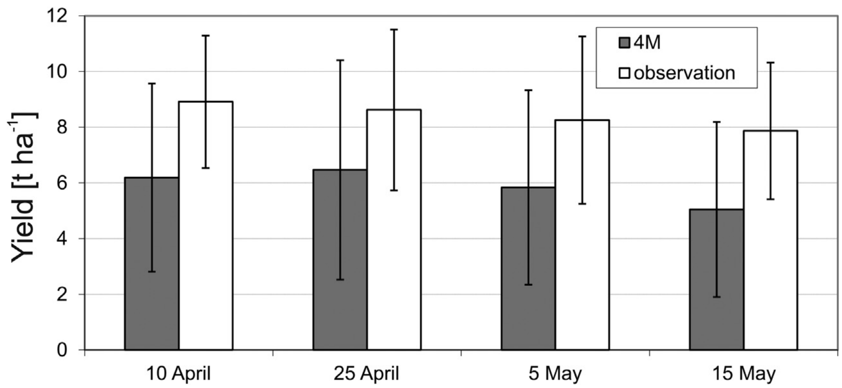

Fig. 2. Comparison of observed and simulated yields from the Martonvásár PD experiment. Four different dates were used for 13 years. The columns show the mean simulated and observed yield for the experiment. Error bars show plus-minus one standard deviation.

Table 5
Statistical evaluation of the PD methods and the observations for maize for the subset of the country where the observations were available (Fig. 1). The results of the Kolmogorov-Smirnov statistic (D) refer to the comparison of the given method and the observation (OBS), and prob refers to probability. The number of outliers for a given time window refers to the number of PD estimations outside of the predefined interval (see text).

method	mean	median	standard deviation	minimum	maximum	5 percentile	95 percentile	D	prob	Number of outliers in 2001–2010	Number of outliers in 1951–2013
M-1	61	63	21	1	103	28	91	1.00	0	10	63
M-2	76	78	15	28	105	43	92	0.97	0	9	60
M-3	90	90	13	43	127	73	109	0.85	0	7	42
M-4	86	89	13	43	123	66	105	0.90	0	8	51
M-5	100	100	13	66	138	79	122	0.66	0	2	12
M-6	106	107	15	47	141	83	126	0.52	0	1	8
M-I	122	125	15	81	172	96	142	0.34	0	0	5
M-II	127	131	17	81	178	96	147	0.50	0	3	16
M-III	123	125	15	81	172	96	142	0.36	0	0	5
M-IV	126	128	13	84	172	98	143	0.44	0	1	7
M-V	117	120	13	79	150	94	134	0.16	0	0	4
M-VI	112	110	14	80	143	85	132	0.36	0	1	7
M-VII	112	111	14	80	143	85	132	0.33	0	1	6
M-VIII	112	113	13	78	148	91	131	0.28	0	1	4
OBS	118	118	8	93	134	104	129	–	–	–	–

from the origin was calculated. The method providing the minimum distance was selected as the optimal, suggested method.

In the second criteria a method was sought which estimated the static PDs used by 4M (20 April for maize and 15 October for winter wheat) best. The method satisfying the second criteria can be used in crop yield estimations that are comparable with the fixed day method used by 4M by default.

2.7. Calculation of crop yields with 4M

4M model was used to simulate the PD experiment at Martonvásár. The model was initialized with the default settings described above, without any further adjustment in the management except the observed PDs.

Yield projections were calculated for Hungary by using the 4M crop model with fixed, and with the best weather dependent PDs for the 2014–2100 period. For the simulations atmospheric CO_2 concentration was set based on the A1B scenario up to 2100.

All 10 RCM results (see Table 1) were used to estimate possible yield changes for the future. Spatial averages were calculated based on the simulations on annual basis.

3. Results

3.1. Validation of the 4M model

Validation of the 4M model with the fixed PD was performed against observed yields in the study of Fodor (2012) and Fodor et al. (2014). In the previous studies the model performance was characterized by statistical indicators. Bias (mean signed error) was -0.075 and $-0.067\,t\,ha^{-1}$, root mean square error (RMSE) was 1.11 and $0.99\,t\,ha^{-1}$, mean relative error (MRE) was 16.4 and 15.9%, square of the linear correlation coefficient (R^2) was 0.82 and 0.83 for maize and winter wheat, respectively.

In this study, validation based on data from the Martonvásár site during period 2001–2013 showed that the model underestimated the observed yields of maize, on average, while it captured the overall decrease of yield with later PD (Fig. 2). 4M simulated higher yield variability than observations showed, especially for the earliest 2 dates (not shown).

3.2. Validation of existing planting date methods

Tables 5 and 6 show that the estimation methods M-1–M-6 and W-1–W-2 generated considerably different PDs. For maize, the M-1–M-6 methods produced too early PDs, especially when the threshold for air temperature was too low (8 or 10 °C). This fact along with a high number of outliers during 2001–2010 and 1951–2013 led us to the rejection of all 6 methods.

For winter wheat the method with single-day air temperature threshold (W-1) gave too early PDs compared to the acceptable time-window (Table 6). Using the criterion on number of allowed outliers (2001–2010 and 1951–2013), the W-1 method was rejected.

The W-2 method gave considerably smaller spatial variation than W-1 (not shown here). Based on the database of historical PD

Table 6
Statistical evaluation of the PD methods and the observations for winter wheat in the subset of the country where the observations were available (Fig. 1). The results of the Kolmogorov-Smirnov statistic (D) refer to the comparison of the given method and the observation (OBS), and prob refers to probability. The number of outliers for a given time window refers to the number of PD estimations outside of the predefined interval (see text).

method	mean	median	standard deviation	minimum	maximum	5 percentile	95 percentile	D	prob	Number of outliers in 2001–2010	Number of outliers in 1951–2013
W-1	263	263	11	206	289	250	279	0.88	0	4	15
W-2	278	279	8	251	292	262	288	0.57	0	1	5
W-I	287	286	8	269	319	278	304	0.33	0	0	0
W-II	288	286	10	269	343	278	306	0.32	0	3	12
W-III	285	284	9	250	332	275	303	0.40	0	1	8
W-IV	281	283	9	249	332	266	295	0.48	0	0	4
OBS	291	293	10	261	315	273	307	–	–	–	–

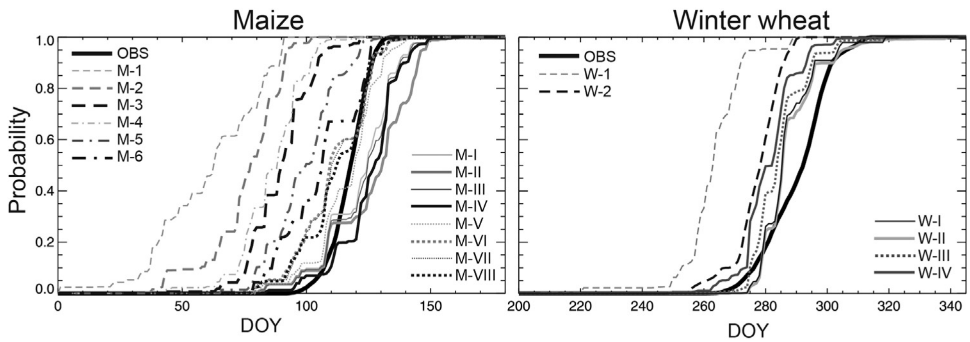

Fig. 3. The cumulative distribution functions (CDFs) of both already existing (Table 3) and newly developed (Table 4) PD estimation methods for maize and winter wheat for the 2001–2010 period in the locations where observations were also available (Fig. 1).

records, farmers in the southern part of Hungary tend to sow wheat 5–7 days later than farmers in the northern territories. This spatial variation was not captured by W-2 most likely due to a conservative parameter that is air temperature of the coldest month (aTc) used by W-2 (Table 3). Hence, the W-2 method was also rejected.

3.3. Validation of the new planting date methods

Tables 5 and 6 show the statistical evaluation of the newly introduced PD methods.

The testing of different air temperature thresholds showed that setting daily average temperature above 12 °C for 7 consecutive days before maize planting (M-I) gave acceptable results (Table 5). The inclusion of precipitation in the estimation (M-II) resulted in larger variability and the estimated PDs were out of the predefined time-window in many years (during 2001–2010 and also during 1951–2013; Table 5). Therefore, M-II was rejected. When soil moisture was used instead of precipitation (M-III), the variance decreased and the performance of the method improved. Of the M-IV – M-VIII methods, which also use the soil temperature, M-IV and M-VI had too many outliers and were therefore rejected.

Although the calculated dates generally remained within the defined time window, when these dates were compared to the PD used by 4M (20 April; doy 110), M-I–M-III all exhibited overestimation of PD. The additionally involved, fine-tuned methods (M-V, M-VII and M-VIII) came closer to the fixed PD (in terms of means) owing it to the modified temperature values and periods. Regarding to the average PDs the M-VII, and M-VIII showed the best fit to 20 April (2 days difference; Table 5).

In case of winter wheat even the simpler W-I method was able to provide acceptable PD estimations considering the predefined time window (Table 6). Adding a condition on soil moisture (W-II–W-IV) ensures that the calculated date reflects the farmers' practice more realistically in terms of possibility for field operation with the machinery. All 4 new methods show underestimation of the mean observed date. W-II and W-III are rejected due to the higher number of outliers, despite of W-II estimated the fixed date exactly in term of means. W-IV gave 7 days difference to 15 October (doy 288).

3.4. Distribution of estimated and observed planting dates

Fig. 3 shows the cumulative distribution functions (CDFs) of the PDs provided by the estimation methods for maize and winter wheat, and that of the observations. In case of the literature based methods the difference between the distributions is rather obvious. The distribution of the novel methods approaches the observations better, though the shape of the CDFs is different.

The Kolmogorov-Smirnov statistic showed that the maximum distance between the cumulative distribution of the observations and the simulations was quite large for the literature based methods (approaching 1 for M-1 and M-2) but it was smaller for the novel methods. In the latter case, maximum distance is typically less than 0.5, and it is only 0.16 for M-V.

Significance level of the Kolmogorov-Smirnov statistic was zero for each existing and novel methods. It means that the distribution of the observed and simulated PD dataset differed significantly.

3.5. Ranking of the accepted planting date estimation methods

A two dimensional decision space was constructed based on the differences of the mean estimated and simulated PDs (x axis) and the number of outliers (y axis). Note that differences of medians gave similar results.

Square of linear correlation coefficient between number of outliers during 2001–2010 and 1951–2013 was very high (0.99 for both maize and wheat) thus we used the number of outliers during the 1951–2013 time period. In the 2D decision space an accepted method was thus represented by a point. Euclidian distance (d) between the point and the origin was calculated.

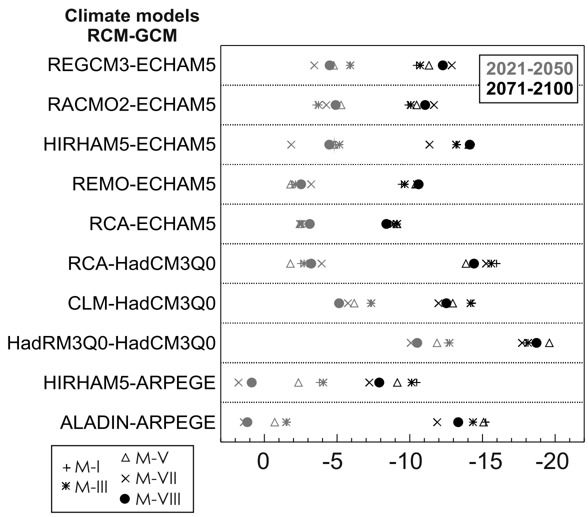

Fig. 4. Maize PD shifts projected by the ten regional climate models for the period 2021–2050 and 2071–2100 compared to the period 1961–1990. Different symbols represent different methods (Table 4).

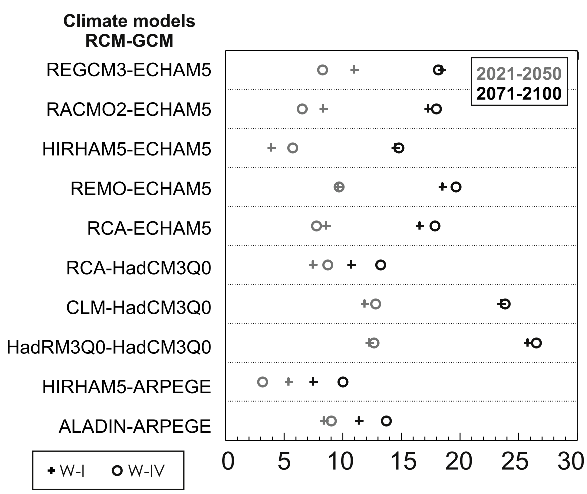

Fig. 5. Winter wheat PD shifts projected by the ten regional climate models for the period 2021–2050 and 2071–2100 compared to the period 1961–1990. Different symbols represent different methods (Table 4).

In case of maize the distance was the smallest in case of the M-V method ($d = 1.0$), while the second best method was M-I ($d = 4.0$). The distance was the largest for the M-VIII method ($d = 6.5$).

For winter the best method was W-I ($d = 4.0$), while the second best was W-IV ($d = 10.2$).

3.6. Projections for the future

3.6.1. Planting date

PDs were calculated using the seven accepted, newly developed methods (all methods in Table 4 except M-II, M-IV, M-VI and W-II, W-III) based on the FORESEE database for the 2014–2100 period using the 10 different climate projections.

The selection of the RCM used for creating the future meteorological data has an order of magnitude greater effect on the PD shift than that of the PD method selection (Figs. 4 and 5).

If PD estimates driven by the 10 climate models are compared for maize, the difference between the maximum and the minimum of the date shifts was 11 and 10 days for the 2021–2050 and the 2071–2100 periods, respectively (the presented values were rounded to integers). The same difference for winter wheat was 9 and 17 days for the 2021–2050 and the 2071–2100 periods, respectively.

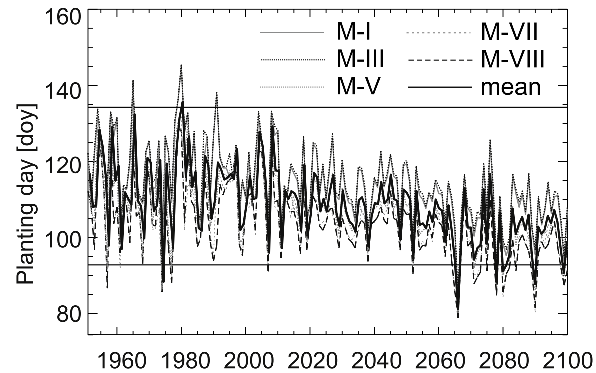

Fig. 6. PDs for maize based on the five accepted methods (see Table 4) for the period 1951–2100. One line per method shows the spatially averaged dates for Hungary. Black solid line shows the average of the five methods. For the future (after 2014) the multi-climate-model mean was plotted. Horizontal solid lines represent 3rd of April and 14th of May.

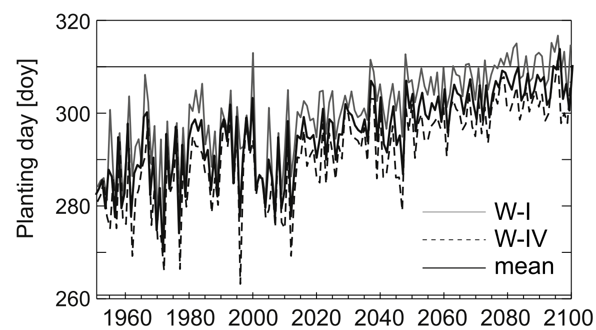

Fig. 7. PDs for winter wheat based on the two accepted methods (Table 4) for the period 1951–2100. One line per method shows the spatially averaged dates for Hungary. Black solid line shows the average of the two methods. For the future (after 2014) the multi-climate-model mean was plotted. Horizontal solid lines represent the 18th of September and 11th of November.

For maize, the difference between the maximum and the minimum PDs estimate shifts caused by the method selection was 2 and 1 days for the 2021–2050 and the 2071-2010 periods, respectively. For winter wheat, this difference was 0 day for 2021–2050 and 1 day for 2071–2100.

Considering the average of the results based on the different RCMs, the accepted methods estimated earlier PDs for the future in case of maize. The magnitude of the shift is 4 days for the near future (2021–2050) and 12 days for the distant future (2071–2100) on average for Hungary (Fig. 6). Different methods gave quite similar magnitude of shift. The standard deviation of inter-climate model differences is 3 days in both periods.

In case of the winter wheat, the PD averages are projected to shift towards later dates (Fig. 7) by 9 ± 3 days for the period 2021–2050 and 17 ± 5 days for 2071–2100 compared to 1961–1990. The shift is larger by about 4 days for wheat than for the maize.

For both crops the coefficients of variation (the ratio of the standard deviation and the mean) shows that almost all of the methods – with one exception – estimate greater shift than the standard deviation caused by the climate model selection.

3.6.2. Yield

As we showed, the fine-tuned M-VII and M-VIII methods are both suitable for the comparison of yield projections using fixed dates and weather dependent dates as they approximate the 4M default settings well. Taking into account the yield simulations for the period 1990–2013 (country mean) M-VIII gave $-0.05\ \mathrm{t\,ha^{-1}}$

difference, while M-VII showed $-0.18\,t\,ha^{-1}$ difference when compared to the fix-day method. Based on these results the M-VIII was selected for the future yield simulations.

In case of winter wheat both W-III and W-IV are suitable for the comparison with the fixed day approach. Simulated yield based on W-III differed from the fix-day method by $-0.84\,t\,ha^{-1}$, while in case of the W-IV the difference was only $0.04\,t\,ha^{-1}$ (period 1990–2013, country average), thus we used the W-IV method for yield based comparisons for the future.

Both the weather specific and the fixed PD methods showed decreasing maize yields in the future (Fig. 8); the decrease was greater with fixed PD method. The simulated maize yields for the period 2021–2050 were 4.9 ± 0.9 and $5.4 \pm 0.8\,t\,ha^{-1}$ in case of the fixed and the weather dependent PD methods, respectively. For the end of the century the estimated yields were 3.6 ± 1.1 and $4.4 \pm 1.1\,t\,ha^{-1}$, respectively. The estimated rates of change were $-0.25\,t\,ha^{-1}\,decade^{-1}$ and $-0.17\,t\,ha^{-1}\,decade^{-1}$ in case of the fixed PD and the M-VIII method, respectively. The average differences between the yields obtained with the fixed and the climate specific PD simulations are increasing in time for maize. The estimated rate of change of the difference between the methods was $0.08\,t\,ha^{-1}\,decade^{-1}$.

In case of winter wheat, the multi-climate model average estimated a slight yield increase for the future. However, the interannual variation of yields was projected to increase as well. In most years the fix-day method generated higher yields (Fig. 8). For 2021–2050 the simulated yields for the winter wheat are 4.9 ± 0.5 and $4.8 \pm 0.5\,t\,ha^{-1}$ in case of the fixed and the weather dependent PD methods, respectively. For the 2071–2100 period these values are 5.55 ± 0.6 and $5.2 \pm 0.7\,t\,ha^{-1}$ in the same order. The estimated rates of change were $0.11\,t\,ha^{-1}\,decade^{-1}$ and $-0.07\,t\,ha^{-1}\,decade^{-1}$ in case of the fixed PD and the W-VIII method, respectively. The difference between the methods slightly decreases, by $-0.03\,t\,ha^{-1}\,decade^{-1}$.

4. Discussion

4.1. Applicability of 4M

Previous studies indicated that 4M is able to provide realistic yield estimations for Hungary (Fodor, 2012; Fodor et al., 2014). Other crop models show similar performance at larger spatial scales (Moriondo et al., 2011; Liu et al., 2013). However, site-level performance of state-of-the-art crop models is rather variable (Rötter et al., 2012; Martre et al., 2014; Li et al., 2015). Difficulty of current crop models to provide reliable results at point scale is associated with the variability of meteorological conditions, soil characteristics, management practices and the planted cultivars. Additionally, errors associated with model structure are common in crop modelling (Bassu et al., 2014; Martre et al., 2014) and options for small-scale parameterization are also limited at small scales.

Nevertheless, the results obtained at Martonvásár experiment indicate that the 4M model is suitable to capture yield variability related to PD definition in the long term. Observations indicate that yield systematically decreases in case of maize due to the later planting (Fig. 2).

4M was able to reproduce this tendency, though the simulated yields were systematically underestimated. This latter phenomenon can be explained by the uncertainty caused by fertilization, different cultivars, sub-grid scale precipitation pattern and other unresolved effects.

Ability of 4M to reproduce the dependence of yield on PD ensures that the climate change related simulations might be usable for decision making.

4.2. Planting date

Novel, weather dependent PD estimation methods were developed and assessed in this study together with several published methods.

The existing global, climate driven PD calculation methods performed poorly on regional scale. The published methods gave too early dates for the study area both for maize and winter wheat. The previously published methods which use only single-day air temperature threshold become less and less adequate due to the growing frequency of extreme weather events (Beniston et al., 2007). The multiple-day limit for air temperature seems to be a more useful principle providing more accurate results.

New, more reliable methods were developed to provide PDs for this region. In case of maize with a simple reparametrization (changing the 7-day air temperature requirement from 10 °C to 12 °C) an acceptably good method were created. On the other hand, in real life decisions, farmers also take the soil moisture conditions and the soil temperature into account.

Introduction of soil moisture in planting related decisions is rather straightforward, as farmers have to avoid too wet soil conditions, when the tractors cannot be used in the field due to the mud (Rotz and Harrigan, 2005; suitable days are estimated by the so-called field operation conditions (FOC) in Eitzinger et al., 2012).

Some of the methods that use the latter criterion were found to perform well in terms of match with a predefined time window, and some were rejected on this basis (M-II, M-IV and M-VI). Additionally, when the average PDs were examined for past together with the number of outliers, M-V method gave the best fit to the observed average PDs (Table 5).

M-VIII method gave back most accurately the average fixed PD previously used with 4M (DOY 110) as well as the simulated yield for the period 1990–2013 for Hungary in comparison with the yield obtained by the fixed date approach. Thus M-VIII method is useful if yield is the focus of the study, e.g. in relation with adaptive agriculture.

In case of winter wheat, W-I and W-IV gave acceptable estimations considering the time window. Because of the field operations it is probably fair to say that the W-IV method is preferred in spite of its worse performance in statistical sense in comparison with W-I.

Considering the distribution of the PDs, none of the methods was able to reproduce the observations. As we seek for methods that are usable in general, and can provide PDs within a possible time windows, such a lack of match in distributions should not limit the applicability of proposed methods.

However, this dissimilarity indicates that our climate dependent methods do not simulate the subjective decisions of the farmers well. This can be explained by the real-life practice of the farmers. In case of suitable conditions for sowing, the farmer might decide to wait a few days before sowing for many reasons. Availability of machinery or occupation of the farmer might delay the planting. In many cases sowing is not completed during one day, which also causes deviation from our simple models. Other reasons might also interact with the timing of planting. Future studies might aim to create more complex methods that can reconstruct the observed distribution of PDs. Probabilistic methods might help which allow flexibility in the beginning of the possible time window for sowing but become strict later.

4.3. Projected future variations in planting dates

Our research indicated climate change-induced changes in PDs for both investigated crops. Maize and winter wheat were projected to be sown around two weeks earlier and later in average, respectively, by the end of the 21th century in Hungary (Figs. 6 and 7). This

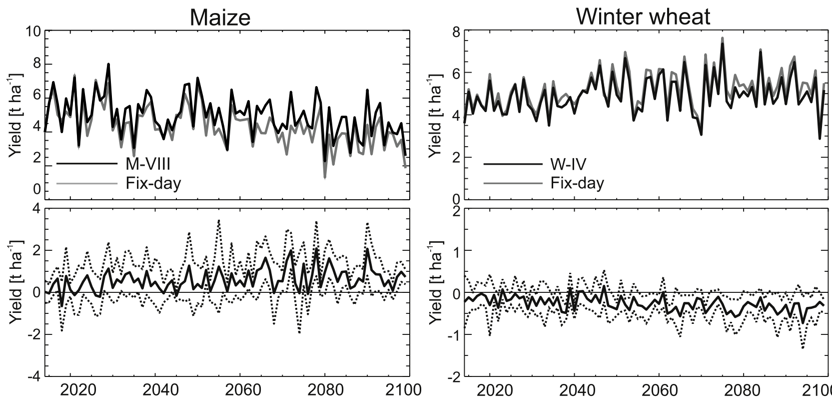

Fig. 8. Simulated annual yields for the period 2014–2100 based on the spatial and multi-model mean using a climate-dependent (M-VIII and W-IV) and a fix-day PD method (20th of April and 15th of October). Upper graphs show the annual yield based on the two methods. Bottom graph shows the yield differences between the two methods and the standard deviation of the climate models (dotted lines).

agrees with Alexandrov and Hoogenboom (2000), who showed that planting of maize in the North-East Bulgaria shifts at least 2 weeks earlier in the 2080s under the ECHAM5 climate model scenario. In spite of the relatively small mean shift the adaptive planting has a detectable and clear effect on the projected yields (Fig. 8).

Prolongation of the growing period does not necessarily mean that environmental conditions for plant growth will be optimal. For example, Eitzinger et al. (2012) pointed out that planting conditions during spring could deteriorate due to increasing winter precipitation, thus increasing soil wetness in East Central Europe.

The interannual variability of PDs based on the individual models is projected to decrease based on 9 models for the period 2021–2050 and 8 models for 2071–2100 in case of the maize. For the winter wheat 5 models estimate decreasing variability for 2021–2050 and 7 for 2071–2100.

For both crops almost all of the methods (with one exception) estimate greater mean shift than the standard deviation caused by the climate model selection. This result suggests that our findings can be considered as robust estimations, when the variability caused by climate model selection is smaller than the signal of PD change.

4.4. Expected changes in crop yield due to environmental change

In the agricultural sector adaptation to climate change contains adjustment of management practices including the PD, optimal selection of cultivars, change in tillage practices, timing and amount of applied fertilizers, irrigation, and pesticides (Olesen et al., 2007, 2011; Eitzinger et al., 2012). Optimized management helps mitigating the negative effect of climate change maintaining or increasing crop yield and yield stability (Alexandrov et al., 2002; Lobell et al., 2008; Liu et al., 2013; Waongo et al., 2015).

The introduced PD methods are based on the expected climate and it is realistic to assume that farmers will adapt to the changing climatic patterns. Consequently, the application of weather dependent sowing date methods in climate change impacts studies seems to be inevitable.

The major issue is that yield is related to the PD even in present day conditions (Fig. 2; Torriani et al., 2007). This observation and model based evidence claims for further decisions on PD adaptation.

Our results indicate that the selection of sowing method (i.e. applying or neglecting the alternative, weather dependent PD methods) is not a simple issue. In case of maize the new methods might result in higher yields in comparison with the currently applied fixed day method (where the latter is of course not fixed in reality but fluctuates within given dates). On the contrary, sowing winter wheat within the currently used time interval seems to provide larger yields in the future than the method which uses PDs estimated with the introduced methods.

The projected maize yield loss seems to be connected with warming climate and the overall summer drying, which can be mitigated with earlier sowing. The warming climate speeds up the growing processes of maize, which leads shorter growing period as well as shorter time for photosynthesis and grain filling (Nielsen et al., 2002; Liu et al., 2013). Previous studies suggested that earlier PDs and cultivars with higher thermal time requirements could avoid the negative effects on maize yield (Torriani et al., 2007; Liu et al., 2013).

The evaluated climate projections indicated that spring precipitation will not show substantial changes in the future, while there is a concordance of predictions that summers will become drier in the Carpathian Basin (Dobor et al., 2013 and in other studies; see Pongrácz et al., 2011; Bartholy et al., 2013). Our results agree with other studies where it was shown that increasing water deficit is expected to cause maize yield loss in the future for the Pannonian and Mediterranean region (Olesen et al., 2011; Eitzinger et al., 2012). Early sowing in case of maize might be better in order to avoid the drought effect especially on flowering, which will be feasible due to the gradually warming spring periods.

Winter wheat is affected by the summer drought to a much smaller extent in Hungary due to the harvest in end of June/beginning of July. Though the increasing average autumn air temperature facilitates later sowing, it may results lower yields. The plants sown later have less time to grow strong before the winter and start the intensive growth from a retarded stage after the dormancy period. Our findings are in accordance with Torriani et al. (2007) who studied the possible effects of climate change on crop yield for Switzerland. They found that the PD shift is beneficial only for maize yield but not for winter wheat. Vanuytrecht et al. (2016) documented similar results for Belgium.

The presented results are based on a few assumptions and simplifications that need to be mentioned. As our aim was to quantify the relationship between PDs and yield, static management and crop genotype was used to avoid interaction between the other management options and yield. In the future improved crop genotypes will likely be introduced to avoid the negative effects of climate change (Donatelli et al., 2015). In this sense our results are affected by the selection of the crop genotype. If information will be available on the widespread application of new cultivars in Central Europe the simulation has to be repeated as the response of plants to e.g. drought can change. Also, length of phenophases can change with the new cultivars that are known to be sensitive to the environmental conditions (Alexandrov and Eitzinger, 2005;

Vanuytrecht et al., 2016). In the future re-evaluation of this issue will be necessary to keep track with changes in our environment and cultivar choice.

In the present modelling exercise harvest and fertilization dates were varied according to the change on PD (number of days between sowing and other management dates were static). Amount of applied fertilizers was static in the simulations. We neglected irrigation options completely. According to the projected summer drying (Pongrácz et al., 2011), irrigation seems to be a feasible option to decrease yield loss. Future studies might include irrigation and fertilization related adaptation strategies, and also improved management options might be considered once information on the adaptive management techniques that farmers use will be available.

5. Concluding remarks

Our results showed that usage of fixed PDs for long-term model simulations as well as for climate change related model studies might not be advised as the factual PD is expected to change in time as it depends on actual meteorological and soil conditions.

Using fixed PDs in yield projections may result in over- or under-estimations of climate change induced yield-losses by tonnes.

Considering adaptive agriculture in Central Europe, the recommended method for maize planting is the newly introduced M-V, which means that before sowing the average daily air temperature and the temperature of the upper soil should be higher than 12 and 10 °C (respectively) for 5 consecutive days, and the soil should be in appropriate moisture condition for field operation. M-I method might also be applicable, if only the average air temperature is available for the PD calculation (i.e. planting should happen when daily mean air temperature is higher than 12 °C for 7 days).

In case of winter wheat farmers should select an appropriate day between 25 September and 11 November when soil conditions are not too dry or wet. No further conditions should be considered, at least according to our results. It means that although the warming climate might allow later planting, the farmers should not change dates.

Our study can be a guide for crop simulation experiments to establish realistic, weather- and soil-specific planting calendars for Hungary including adaptive management strategies in a wider context. For example, summer drying – that seems to be a consistent projection in the RCM results that FORESEE uses – claim for developments of irrigation. Location, timing and amount of irrigation water need to be prescribed to the model to provide yield projections. Crop models like 4M can be used to optimize the irrigation need of vulnerable regions to minimize cost and maximize income for the farmers.

Though the present study focuses on Hungary, the results might be generalized to the wider European context. Climate change is projected to affect different parts of Europe in heterogeneous fashion (Van der Linden and Mitchell, 2009; Christensen and Christensen, 2007) but similarities exist in some regions like Central-Eastern Europe or the Mediterranean Basin. Similar studies are strongly needed in other regions to address the questions related to adaptive agriculture with consequences on economical growth and sustainable development.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.agrformet.2016.03.023.

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