Agricultural Systems 120 (2013) 61–75

Contents lists available at SciVerse ScienceDirect

Agricultural Systems

journal homepage: www.elsevier.com/locate/agsy

Pan-European crop modelling with EPIC: Implementation, up-scaling and regional crop yield validation

Juraj Balkovič [a,c,*], Marijn van der Velde [a], Erwin Schmid [b], Rastislav Skalský [a,d], Nikolay Khabarov [a], Michael Obersteiner [a], Bernhard Stürmer [b,e], Wei Xiong [a]

[a] International Institute for Applied Systems Analysis (IIASA), Ecosystem Services and Management Program, Schlossplatz 1, A-2361 Laxenburg, Austria
[b] Institute for Sustainable Economic Development, University of Natural Resource and Life Sciences, Vienna, Feistmantelstrasse 4, 1180 Vienna, Austria
[c] Faculty of Natural Sciences, Comenius University in Bratislava, 842 15 Bratislava, Slovak Republic
[d] Soil Science and Conservation Research Institute, 827 13 Bratislava, Slovak Republic
[e] Austrian Compost and Biogas Association, Franz-Josefs-Kai 1, 1010 Vienna, Austria

ARTICLE INFO

Article history:
Received 2 November 2012
Received in revised form 29 April 2013
Accepted 30 May 2013
Available online 3 July 2013

Keywords:
EPIC
Large-scale crop modelling
Model performance testing
EU

ABSTRACT

Justifiable usage of large-scale crop model simulations requires transparent, comprehensive and spatially extensive evaluations of their performance and associated accuracy. Simulated crop yields of a Pan-European implementation of the Environmental Policy Integrated Climate (EPIC) crop model were satisfactorily evaluated with reported regional yield data from EUROSTAT for four major crops, including winter wheat, rainfed and irrigated maize, spring barley and winter rye. European-wide land use, elevation, soil and daily meteorological gridded data were integrated in GIS and coupled with EPIC. Default EPIC crop and biophysical process parameter values were used with some minor adjustments according to suggestions from scientific literature. The model performance was improved by spatial calculations of crop sowing densities, potential heat units, operation schedules, and nutrient application rates. EPIC performed reasonable in the simulation of regional crop yields, with long-term averages predicted better than inter-annual variability: linear regression R^2 ranged from 0.58 (maize) to 0.91 (spring barley) and relative estimation errors were between ±30% for most of the European regions. The modelled and reported crop yields demonstrated similar responses to driving meteorological variables. However, EPIC performed better in dry compared to wet years. A yield sensitivity analysis of crop nutrient and irrigation management factors and cultivar specific characteristics for contrasting regions in Europe revealed a range in model response and attainable yields. We also show that modelled crop yield is strongly dependent on the chosen PET method. The simulated crop yield variability was lower compared to reported crop yields. This assessment should contribute to the availability of harmonised and transparently evaluated agricultural modelling tools in the EU as well as the establishment of modelling benchmarks as a requirement for sound and ongoing policy evaluations in the agricultural and environmental domains.

1. Introduction

Crop models were developed at the field scale to integrate and quantify biophysical process-based understanding and improve crop production (Bouwman et al., 1996). Gradually, many of these models have expanded to include the external effects of agricultural production on the environment. Although crop models were developed under assumption of homogeneous field conditions, they have been used at farm, regional, national, continental and global levels. Large-scale implementations of crop models are increasingly used for crop growth modelling (Folberth et al., 2012; Liu, 2009; Tan and Shibasaki, 2003) and global policy issues where agriculture plays an important role, including climate change (Challinor, 2009; Liu et al., 2013; Niu et al., 2009), carbon sequestration (Billen et al., 2009), water resources use (Liu and Yang, 2010; Wriedt et al., 2009a), sustainable biofuel production

* Corresponding author at: International Institute for Applied Systems Analysis (IIASA), Ecosystem Services and Management Program, Schlossplatz 1, A-2361 Laxenburg, Austria. Tel.: +43 2236 807 385; fax: +43 2236 807 599.

E-mail addresses: balkovic@iiasa.ac.at, balkovic@fns.uniba.sk (J. Balkovič), velde@iiasa.ac.at (M. van der Velde), erwin.schmid@boku.ac.at (E. Schmid), skalsky@iiasa.ac.at, r.skalsky@vupop.sk (R. Skalský), khabarov@iiasa.ac.at (N. Khabarov), oberstei@iiasa.ac.at (M. Obersteiner), bernhard.stuermer@boku.ac.at, stuermer@kompost-biogas.info (B. Stürmer), xiong@iiasa.ac.at (W. Xiong).

0308-521X
http://dx.doi.org/10.1016/j.agsy.2013.05.008

(Havlík et al., 2011; van der Velde et al., 2009), management intensity and land-use change effects (Schönhart et al., 2011; Stürmer et al., 2013).

The up-scaling of a crop model from field to regional scale involves linking different spatial and temporal scales (cf. Faivre et al., 2004) and provokes practical and theoretical challenges. Firstly, high-performance solutions integrating advanced GIS tools and computing infrastructure are required (Bouraoui and Aloe, 2007; Liu et al., 2007; Nichols et al., 2011). Secondly, integration of spatially heterogeneous soil, weather and management data inevitably leads to aggregation errors resulting in spatial and temporal biases in the yield prediction (Hansen and Jones, 2000). Furthermore, Niu et al. (2009) showed that the use of data from commonly available sources instead of field-measured or location-specific data increases the simulation bias. In addition, the reproducibility of crop model outputs is often difficult as assumptions regarding input data and parameters describing biophysical processes are not always harmonised and documented transparently.

In this study we build and test an EU-wide implementation of crop growth model combining the Environmental Policy Integrated Climate model (EPIC; Williams, 1995) and coarse resolution data that are available at European scale. We report on a comprehensive and transparent validation of this spatial EPIC implementation which is necessary to perform accurate crop model simulations.

Although EPIC has been extensively calibrated and validated against observations under various conditions at the field-scale (e.g. Billen et al., 2009; Cabelguenne et al., 1990; Rosenberg et al., 1992; Schmid et al., 2004; Williams et al., 1989), studies that test crop model performance against spatially extensive time series of regional yields (e.g. van der Velde et al., 2009) as well as crop model sensitivities against climate change (e.g. Strauss et al., 2012) are still rare. The transparent validation of a large-scale crop model implementation is faced with several challenges. Firstly, a thorough model calibration, which is often a prerequisite for its reliable application, cannot be performed since there are no comprehensive experimental or independent data available that allow testing of the entire set of variables and their interactions represented in the integrated model. On the other hand, aggregated data from regional statistics are usually insufficient to derive parameters for crop models as they do not represent field-scale conditions for which the models have been originally developed (Therond et al., 2011). At the same time, it is desired to avoid "feed-back" calibration, the process by which certain model parameters are adjusted randomly until the model outputs fit observed data (Niu et al., 2009). Secondly, large scale crop model simulations can significantly benefit from methodological improvements in spatial and temporal calculations of input variables. Therefore, we (1) accepted the default crop and biophysical process parameter values in EPIC, with only minor, justifiable adjustments, and (2) implemented procedures to calculate potential heat units (PHU), crop sowing densities, nutrient application rates, and field operation timing over time and space. The before-mentioned parameters and variables significantly contribute to uncertainties in EPIC-based estimations and thus have to be carefully evaluated to understand the overall robustness of the model predictions.

The motivation for this study was threefold, first there is a need for transparent, comprehensive, and spatially extensive evaluation of agricultural production using large-scale crop model simulations with sufficient performance and accuracy; secondly, the European Union Member States and the European Commission need agricultural modelling tools that are harmonised and transparently evaluated across the EU. The third motivation relates to the interdisciplinary research activities to integrate biophysical crop model outputs with economic optimisation models describing the land-based production sector (e.g. Leip et al., 2008; Schneider et al., 2011). These types of assessments require the establishment of a reliable crop production baseline reflecting the current input data levels.

The main objective of this article is to evaluate the ability of our Pan-European EPIC implementation to predict long-term average crop yields at a regional level and to reproduce inter-annual variability for four major crops: winter wheat, spring barley, rainfed and irrigated maize and winter rye. To achieve the main objective, several specific objectives were identified: (1) an evaluation and selection of a PET method with appropriate parameter settings with respect to the model's performance, (2) an implementation of an improved method to calculate the spatially explicit distribution of crop sowing densities, (3) a spatially explicit calculation of crop management schedule and nutrient application from chemical fertilizers and manure, and finally (4) to test the model's response and sensitivity to selected meteorological variables and management options.

2. Material and methods

2.1. The EPIC model

The EPIC model was developed by the USDA to assess how agricultural activities affect the status of US soil and water resources (Jones et al., 1991; Williams et al., 1984; Williams, 1990). EPIC compounds various components from CREAMS (Kinsel, 1980), SWRRB (Williams et al., 1985), GLEAMS (Leonard et al., 1987), and CENTURY (Parton et al., 1992), and has been continuously expanded to allow simulation of many processes important in land use management (Sharpley and Williams, 1990; Williams, 1995). The major components in EPIC are crop growth, yield and competition, weather simulation, hydrological, nutrient and carbon cycling, soil temperature and moisture, soil erosion, tillage, and plant environment control. EPIC operates on a daily time step, and can be used for long-term assessments spanning decades to centuries. The model offers options for simulating yields with – *inter alia* – different PET equations, which allow reasonable model applications in very distinct natural areas. Different management options are available, including tillage operations, irrigation scheduling, fertilizer application rates and timing.

In the crop growth routine, potential biomass is calculated daily from photo-synthetically active radiation and radiation-use efficiency. Potential biomass is adjusted to actual biomass through daily stress caused by extreme temperatures, water and nutrient deficiency or inadequate aeration. Crop yields are calculated as a ratio of economic yield over total actual above-ground biomass at maturity as defined by harvest index. Besides meteorological and soil variables, main growth-defining factors are PHU, the biomass-energy conversion factor and the harvest index (Wang et al., 2005). Yield losses due to nutrient stress are mainly controlled by nutrient supplies through crop management. Water stress is effectively controlled through soil water balance, which is especially sensitive to the chosen PET method (Roloff et al., 1998), and supplementary irrigation.

2.2. Data sources at EU scale

Daily meteorological data were obtained from the Joint Research Centre's (JRC) Crop Growth Monitoring System (CGMS) meteorological database (Micale and Genovese, 2004) at a 50 km grid resolution for the period 1995–2007. Land cover information was taken from a combined CORINE 2000 and PELCOM map at 1 km resolution provided by JRC. Digital terrain information was derived from SRTM (Shuttle Radar Topographic Mission; Werner, 2001) and GTOPO sources (Global 30 Arc Second Elevation Data;

http://eros.usgs.gov). Soil data were obtained from the European Soil Bureau Database (ESBD v. 2.0), including the Soil Geographic Database of Europe, the Soil Profile Analytical Database of Europe, the Pedo-Transfer Rules Database, the Database of Hydraulic Properties of European Soils (Wösten et al., 1999) and the Map of Organic Carbon Content in topsoils in Europe (Jones et al., 2005). Administrative regions were obtained from the Geographic Information System of the European Commission (GISCO) and watersheds from the European River Catchment Database, version 2 (ERC; provided by European Environment Agency, http://www.eea.europa.eu). Agricultural statistics on crop yields and fertilizer consumptions were retrieved from the Statistical Office of the European Communities (EUROSTAT) and IFA/FAO datasets (IFA/IFD/IPI/PPI/FAO, 2002). Information on rainfed and irrigated crop areas were taken from the European Irrigation Map (EIM) presented by Wriedt et al. (2009b).

2.3. Integration of EPIC with GIS and up-scaling for large-scale modelling

In order to implement crop growth simulations at European scale, the EPIC model (version 0810) was integrated with ArcGIS using a loose coupling approach (Siu, 1998) as presented in Fig. 1. Programs were connected through data exchange in ASCII file format. ArcGIS capabilities were used for preparation of EPIC input datasets from the above GIS data sources and for rendering output variables. EPIC was run outside of GIS, while the data transfer and file format conversions were automated using Visual Basic. A similar approach has been used for other large-scale EPIC implementations by Tan and Shibasaki (2003), Liu et al. (2007) and Bouraoui and Aloe (2007).

The EU EPIC modelling system was integrated by combining data layers on soil and physiographic aspects of land with watersheds and administrative regions. The site and soil spatial data were linked to the European wide INSPIRE-compliant 1 km modelling grid with Lambert-Azimuthal equal-area projection (Annoni, 2005). To avoid redundant model runs, model grid cells with homogeneous input data were aggregated following a two-step approach (Schmid et al., 2006). First, Homogeneous Response Units (HRU) were defined at 1 km resolution, with homogenous physical properties given by intersections of more-or-less stable site properties such as: (i) elevation classes <300 m, 300–600 m, 600–1100 m, 1100–1600 m, 1600–2100 m, and >2100 m, (ii) slope classes <3%, 3–6%, 6–10%, 10–15%, 15–30%, 30–50%, and >50%, (iii) soil of coarse, medium, medium-fine, fine, very fine, and peat texture (CEC, 1985), (iv) soil depth classes <40 cm, 40–80 cm, 80–120 cm, and >120 cm, and (v) subsoil stoniness classes <5%, 5–25%, and >25%. Subsequently, a zone raster was defined consisting of homogenous Simulation Units (SimU) upon which the model was run. Simulation Units are combinations of one NUTS2 region, one watershed, one land cover and one Homogeneous Response Unit (HRU) at 1 km resolution. A total of 38,738 SimUs for cropland were then linked to 50 km CGMS grid, identifying a representative grid cell for each SimU. Accordingly, each SimU reflects a unique

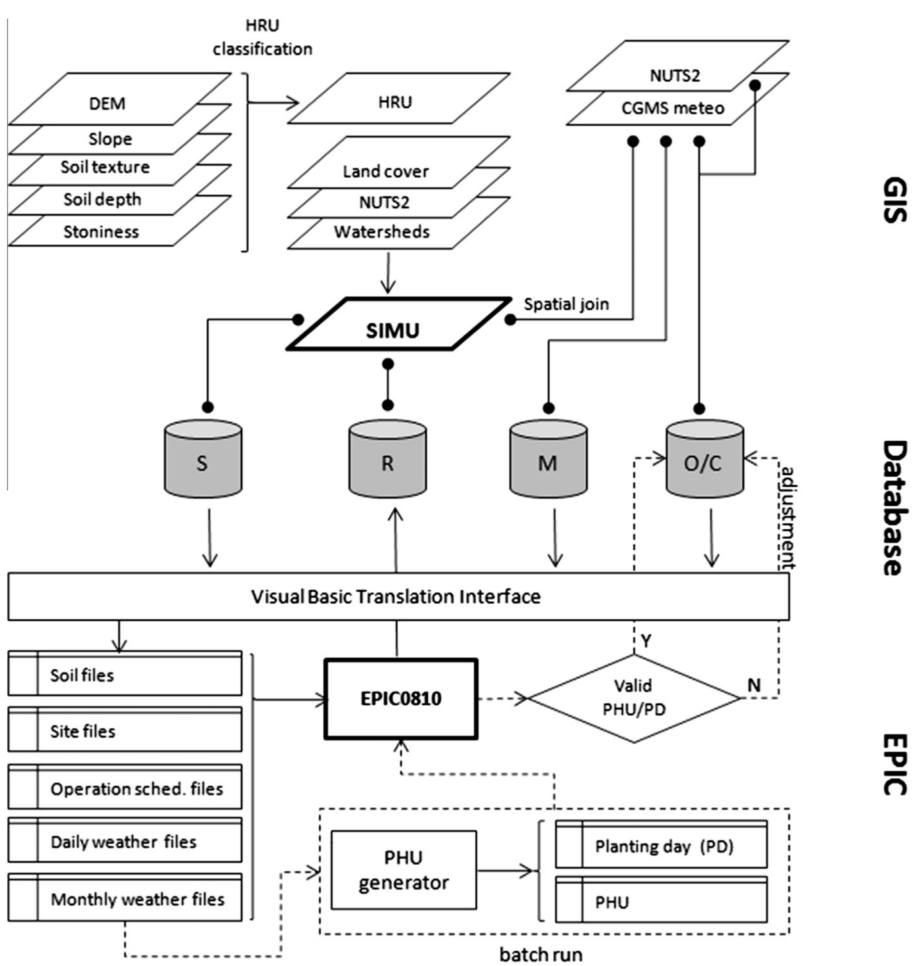

Fig. 1. Schematic diagram of the Pan-European EPIC implementation. S – soil and topographical database, M – meteorological database, O/C – field operation schedule and EPIC control database, R – results database; dashed line denotes EPIC simulations related to optimising PHU and planting dates.

combination of weather, soil type, topographic exposition, and crop management.

2.4. Crop model setup

In total, six daily meteorological variables from the CGMS database were used to run EPIC from 1996 until 2007: minimum and maximum temperature (°C), precipitation (mm), global radiation (MJ m^{-2}), mean vapour pressure (hPa), and mean wind speed at 10 m (m s^{-1}).

Each SimU was attributed with a set of 13 soil properties, including soil organic carbon (%), sand, silt and clay (%), bulk density (g cm^{-3}), base saturation (%), cation exchange capacity and sum of base cations ($cmol_+$ kg^{-1}), pH, stoniness (vol.%), saturated hydraulic conductivity (mm h^{-1}), and wilting point and field water capacity (cm^3 cm^{-3}). All these variables are averages calculated from the ESDB separately for topsoil (0–30 cm) and subsoil (>30 cm) horizons. Additionally to ESDB, pedo-transfer rules published by Balkovič et al. (2007) were used to acquire all soil properties. Soil profiles were split into 10 vertical layers to appropriately address soil water and temperature regimes. In addition, the SimU landforms were approximated with mode slopes and mean elevations obtained from SRTM/GTOPO.

In most large-scale crop model setups only one value is chosen for crop sowing densities across zones with variable climatic conditions, even though it is a critical yield-determining variable (Deng et al., 2012). Here, we calculated and distributed sowing densities for winter wheat, winter rye and spring barley using a method that is novel for large-scale crop modelling applications. Sowing densities were estimated based on expected plant available precipitation and optimum ear density as published by Wichmann (1999). Although sowing densities may vary considerably depending on cultivars and farming system, our values are in line with plant population ranges which have been calibrated for the three crops in EPIC (cf. Williams et al., 2006). Plant available precipitation (mm) was calculated from average monthly precipitation using the USDA Soil Conservation method following Smith (1991) at 50 km resolution. The maize plant population density was set constantly to 5 plants m^{-2}. Crops were simulated in 1-year mono-crop rotations on all the available cropland. Maize was not simulated for Sweden, Finland, Latvia, Lithuania and Estonia as it is not usually grown for grain production.

EPIC requires an estimation of PHUs (°C) accumulated by a crop from its sowing to maturity and a detailed regional description of crop management practices, including timing of individual operations or application of fertilizers and irrigation. PHUs (Appendix, Fig. 1) were determined with the use of the PHU calculator developed at the Texas Blackland Research and Extension Center (BREC, 1990) using long-term minimum and maximum temperatures from CGMS, optimum and minimum crop growth temperatures and the average number of days for the crops to reach maturity (see Table 1). We split the study area into Atlantic, Alpine, Boreal, Continental and Mediterranean climatic zones based on the climatic stratification of Metzger et al. (2005) (cf. Bouraoui and Aloe, 2007) to address regional differences in crop varieties (Appendix, Fig. 2) characterized by different times to maturity (Table 1).

Sowing dates were estimated together with PHUs using the PHU calculator at 50 km resolution. Harvesting dates were then calculated by adding the time to maturity to the sowing date. The time windows given by the sowing and harvesting dates were optimised iteratively with EPIC runs, while PHU fractions reached at the harvesting operation were used to tune planting and harvesting as suggested by Williams et al. (2006). Since harvesting dates are considered as the earliest possible dates of harvest, an automatic harvest was scheduled at 110% and 115% of the calculated PHU for cereals and maize, respectively, to enable flexible harvesting based on annual heat unit accumulation and to take post-maturity drying of crops on the field into account.

Tillage operations were scheduled relative to the sowing and harvesting dates. These practices consisted of mouldboard ploughing and seed-bed preparation three days prior to sowing and offset disking two days after harvesting.

Phosphorus and potassium fertilises were applied as rigid amounts together with tillage operation three days prior to sowing. N fertilisation was triggered automatically until the annual N application rate was reached.

The crop and regional specific annual N, P, and K application rates (kg ha^{-1}) were calculated by computing NUTS2 fertilizer balances. Fertilizer supply was calculated from NUTS2 livestock numbers and excretion coefficients (cf. Albert, 2006; Danneberg, 1999; Galler, 1989; Jahn, 1991; Schechtner, 1991) as well as commercial fertilizer consumptions from EUROSTAT. Crop specific fertilizer demands at NUTS2 level were calculated using crop and forage yields and acreages from EUROSTAT as well as nutrient uptake coefficients (Berger, 1969; De Geus, 1973; Fleischer, 1998; Goetz, 1998; Hege and Weigelt, 1991; Kaas et al., 1994; Loehr, 1990; Ten Have, 1989).

Since the other crops are grown mainly under rainfed conditions, maize is the only crop that is considered to be irrigated in this study. Information on the irrigated area of maize (ha) was taken from the EIM (Wriedt et al., 2009b). Similarly to Liu et al. (2007), Folberth et al. (2012) and Heumesser et al. (2012), we used the automatic irrigation trigger in EPIC to supply water when water stress exceeded 10% on a given day. To ensure sufficient irrigation water supply on irrigated cropland, the maximum annual irrigation volume was set to 500 mm. Irrigated and rainfed cropland was simulated separately. The final maize yield was calculated for each SimU as an average of the two scenarios weighted by respective areas of irrigated and rainfed cropland:

$$Y_j = \lambda_{r,j} Y_{r,j} + (1 - \lambda_{r,j}) Y_{f,j} \qquad \text{for} \quad j = 1, \ldots, n \tag{1}$$

where Y_j (t ha^{-1}) is the average maize yield in SimU j, $Y_{r,j}$ is the yield on the irrigated cropland of the jth SimU, $\lambda_{r,j}$ is the fraction of irrigated area in SimU j, $Y_{f,j}$ is the yield on the rainfed cropland of the j-th SimU and n is the number of SimUs.

2.5. Crop model parameterization

Winter wheat, maize, spring barley, and winter rye are major crops grown in Europe and there are many cultivars with different growth properties and productivity. This fact together with the lack of information on the cultivars' spatial distribution leads to a necessity of introducing significant simplification into the modelling system. We use one set of crop model parameters for each crop, which are provided by EPIC developers, with some minor adjustments (Table 1). The parameters that were modified included the optimum air temperature and the base temperature for maize, which were lowered from 25 °C and 8 °C to 22.5 °C and 6 °C, respectively, as suggested by Cabelguenne et al. (1999). The time needed for crop to reach maturity and PHUs were compiled from different data sources (e.g. FAO, CGMS) separately for major agro-climatic zones to address regional crop varieties (Table 1).

The EPIC model offers different methods to calculate PET. We used the original Hargreaves method (H_o), with coefficient of 0.0023 and exponent of 0.5 as published by Hargreaves and Samani (1985). In order to assess the effect of PET methods on EPIC performance, we also used the modified EPIC Hargreaves method (H_m; Williams et al., 2006), the Penman–Monteith method (PM; Monteith, 1965), the Priestley–Taylor (PT; Priestley and Taylor, 1972), and the Baier–Robertson method (BR; Baier and Robertson, 1965).

Table 1
Important parameters and parameter values by crop and agro-climatic zone.

Crop parameters	Winter wheat	Spring barley	Maize	Winter rye
Optimum air temper. (°C)	15[e]	15[e]	22.5[c]	12.5[e]
Base temperature (°C)	0[e]	0[e]	6[c]	0[e]
Biomass-energy ratio, WA (kg MJ^{-1})	35[e]	30[e]	40[e]	35[e]
Harvest index, HI (mg mg^{-1}) range of HI	0.45[e] (0.42[c]–0.49[n])	0.40[e] (0.32[p]–0.56[n])	0.50[e] (0.45–0.60)[w]	0.40[e] (0.25[l]–0.44[n])
Time to maturity (days)				
Alpine	280	115	165	285
Atlantic	300	160	180	290
Boreal	330	115	205	315
Continental	290	130	155	285
Mediterranean	265	140	155	265
Mean potential heat units (°C)				
Alpine	1860	1270	1710	1770
Atlantic	2380	1660	1720	2450
Boreal	1490	1450	1380	1340
Continental	2150	1630	1700	2020
Mediterranean	2660	1630	1880	3050

[e] EPIC.
[w] Wang et al. (2005).
[c] Cabelguenne et al. (1999).
[p] Petr et al. (2002).
[n] Ellen (1993).
[l] Larcher (2003).

2.6. Evaluation of model performance

Simulated crop yields were compared against EUROSTAT reported yield data between 1997 and 2007. Considering availability of reported yields, winter wheat, winter rye and maize were compared at NUTS2 level, whereas spring barley was evaluated at NUTS0 (country) level. EPIC yield estimates were regionalised for each year as weighted average:

$$\bar{Y}_i = \frac{\sum_{j=1}^{n} Y_{i,j} \cdot A_{i,j}}{\sum_{j=1}^{n} A_{i,j}} \quad \text{for} \quad i = 1, \ldots, m \tag{2}$$

where $\bar{Y}_i$ is the regional average yield for the ith NUTS region, $Y_{i,j}$ is the crop yield in the jth SimU of region i, $A_{i,j}$ is the crop harvested area in the jth SimU of region i, n is the total of SimUs in the ith region, and m is the number of NUTS regions. Simulated crop yields were compared at 12% and 15% water content for cereals and maize, respectively.

A total of five statistical measures were used to evaluate the model performance: (i) linear regression, (ii) Pearson correlation coefficient (r), (iii) Root Mean Square Error (RMSE), (iv) Nash–Sutcliffe efficiency (E) and (v) Relative Error (RE). The goodness of simulation was assessed using the coefficient of determination for linear regression (R^2), which was tested by the F-test, and the regression slope. The Pearson correlation coefficient was used to analyse whether simulated yields adequately captured temporal variability in regionally reported yields (cf. Reidsma et al., 2009). Prior to comparing the 1997–2007 time series of simulated against reported yields, the census regional yields were de-trended using linear regression to correct for technology development. The analysis was generally calculated for NUTS2 regions; however, it was scaled up to NUTS1 for some regions with missing temporal data at NUTS2 level (e.g. Germany). The RMSE between simulated and reported yields, which is a measure of the overall relative error, was calculated as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{m} (\bar{Y}_i - X_i)^2}{m}} \tag{3}$$

where X_i is the reported yield for the ith region, and m is the total number of regions reporting crop yields for a given year.

Relative errors (RE) were calculated by Eq. (4) to examine systematic errors in the EPIC modelling. Given the scale of this study, we assume a |RE| of 30% to be an acceptable limit for reliable results, whereas |RE| > 50% were considered to be extreme errors (Niu et al., 2009).

$$RE_i = \frac{(\bar{Y}_i - X_i)}{X_i} \cdot 100 \quad \text{for} \quad i = 1, \ldots, m \tag{4}$$

In addition to RMSE and RE, the overall performance was characterized by the Nash–Sutcliffe efficiency coefficient (Nash and Sutcliffe, 1970) defined as:

$$E = 1 - \frac{\sum_{i=1}^{m} (X_i - \bar{Y}_i)^2}{\sum_{i=1}^{m} (X_i - \bar{X})^2} \tag{5}$$

The Nash–Sutcliffe efficiencies can range from $-\infty$ to 1. An E value of 1.0 means that simulated crop yields are equal to reported ones, a value of 0 indicates that model predictions are as accurate as the mean of the observed data, and $E < 0$ indicates that the mean of the observed data is a better predictor than the model.

Differences between mean values and standard deviations in simulated and reported yields were statistically evaluated using the two-tailed pair t-test and the F-test, respectively, in STATISTICA software (StatSoft Inc., 2003). The coefficient of variation (CV) was calculated for each NUTS2 regions as a ratio of SD over the mean of annual yields between 1997 and 2007 for both simulated and reported EUROSTAT data.

3. Results

3.1. Comparison between simulated and reported crop yields

The annual crop yields simulated at 1 km resolution are presented in Fig. 2. Simulated crop yield averages for winter wheat, spring barley, winter rye and maize were 4.2, 4.0, 3.6, and 7.4 t ha^{-1} with standard deviations of 1.82, 1.04, 1.42, and 1.39 t ha^{-1}, respectively. Reported average crop yields were 4.9, 3.8, 3.6, and 7.3 t ha^{-1} with standard deviations of 2.3, 1.4, 1.7, and 2.5 t ha^{-1}, respectively. Simulated and reported mean annual yields for spring barley, winter rye and maize were consistent since

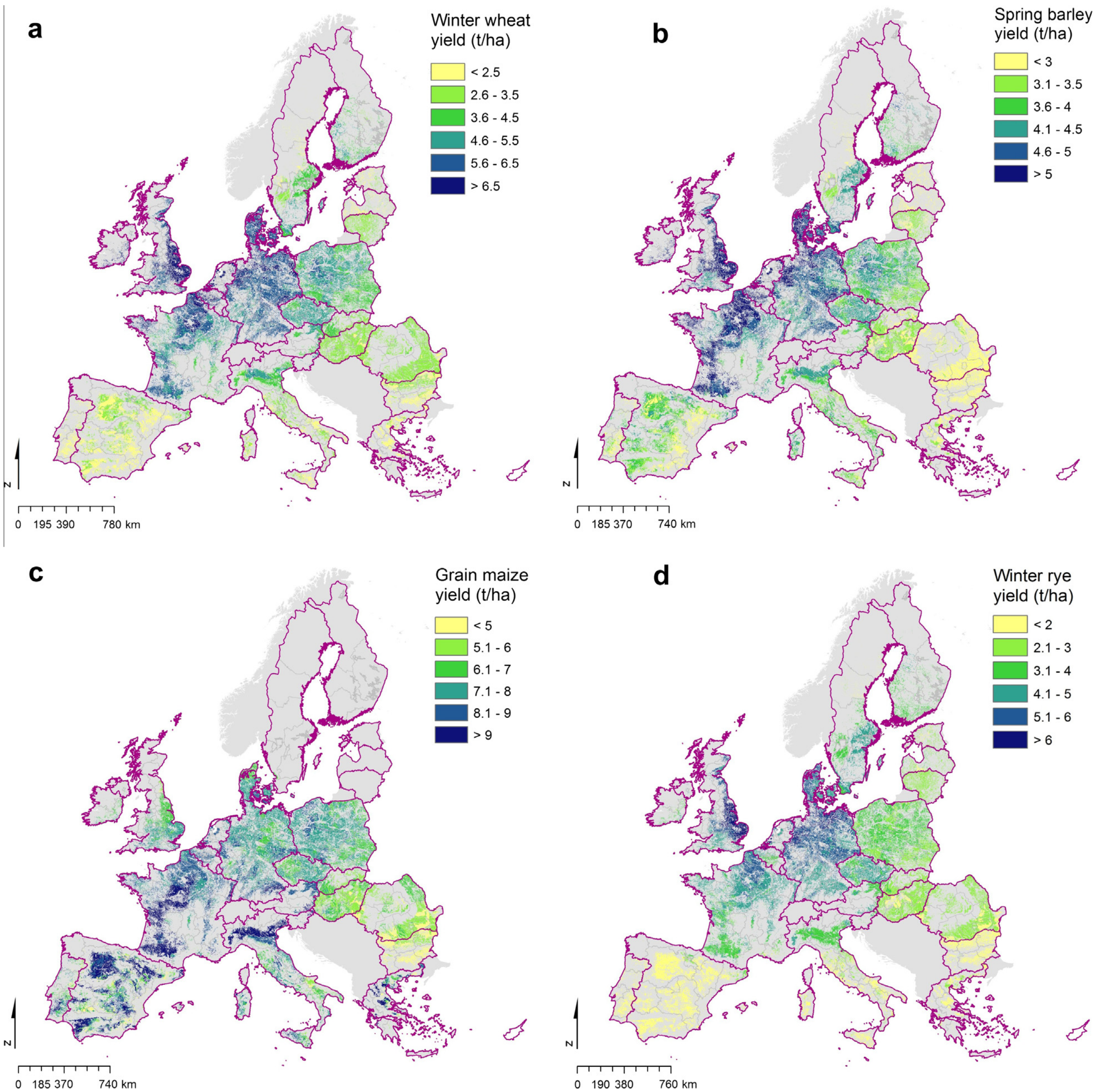

Fig. 2. Predicted average yields of (a) winter wheat, (b) spring barley, (c) grain maize, and (d) winter rye.

the overall yield differences were not significant when tested with the paired *t*-test ($P > 0.05$). The RMSE values varied between 0.5 for spring barley to 1.7 t ha^{-1} for maize. In contrast, EPIC underestimated average winter wheat yields in Europe (the *P* value of the *t*-test less than 0.01) with a RMSE of 1.2 t ha^{-1}. The standard deviations of reported crop yields except for spring barley were significantly higher than of simulated yields (the *P* value of *F*-test less than 0.05).

A comparison between simulated and reported annual yields aggregated at NUTS2/0 level is presented in Fig. 3. The linear regression was highly significant (*F*-test $P < 0.01$) with R^2 between 0.58 (maize) and 0.91 (spring barley). The regression slopes were 0.72, 0.72, 0.43, and 0.75 for winter wheat, spring barley, maize and winter rye, respectively. Therefore, EPIC underestimates yields at higher yield levels and overestimates at lower yield levels. The higher standard deviations in the reported crop yields are clearly visible by comparing the vertical with the horizontal whiskers in Fig. 3. However, note that this pattern can be partly explained by an increasing trend in the reported crop yields due to technical advances, which can be observed in the reported EUROSTAT data of some countries.

The systematic error in the EPIC simulations is presented through the RE maps in Fig. 4. Although no evident regularities are demonstrated in these maps, some general regional pattern can be deduced. Foremost, highly productive regions of Western Europe, including many districts in France, Germany, the Netherlands and Belgium, were especially underestimated for all crops, with RE of less than −10%, or even −20% for winter wheat. In contrast, regions of Eastern Europe, and particularly Romania, Bulgaria and Poland, were generally over-predicted by EPIC. Extreme estimation errors exceeding 50% relative to EUROSTAT yields were observed mainly for maize and winter rye in Eastern Europe, particularly in some regions in Poland, Bulgaria and Romania, and then in Finland and Portugal.

Nash–Sutcliffe efficiencies equal 0.70, 0.85, 0.54, and 0.81 for, winter wheat, spring barley, maize and winter rye and indicate

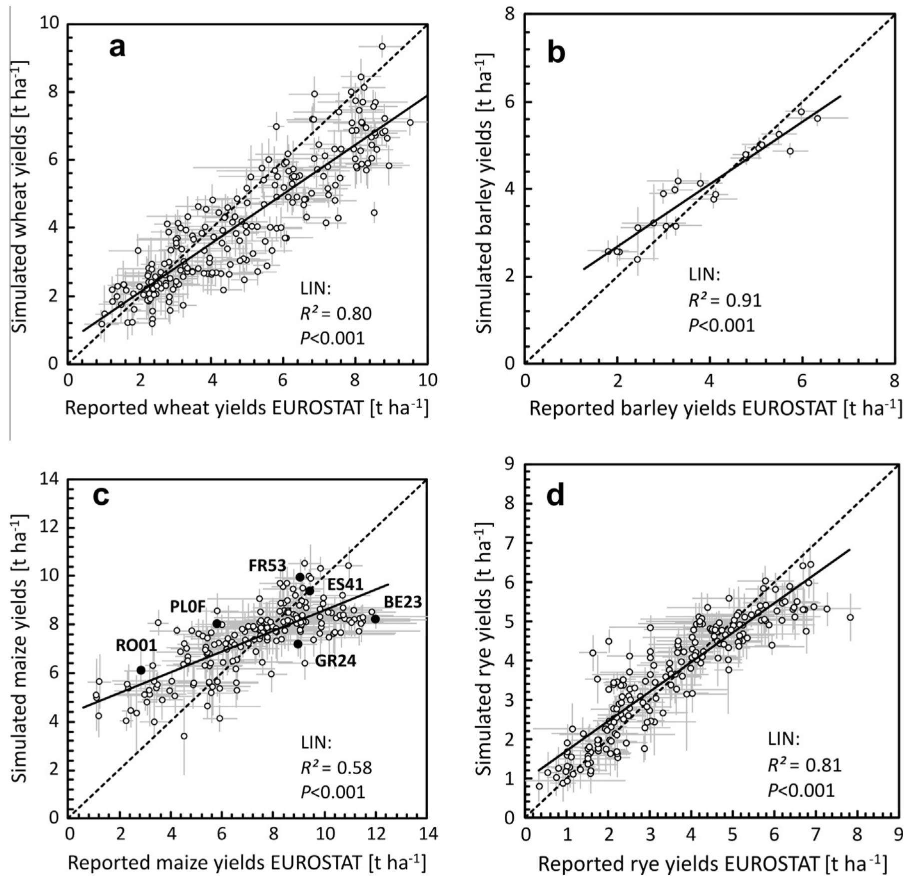

Fig. 3. Scatter plots with means and ±one SD of simulated versus reported regional crop yields (average of 1997–2007) for (a) winter wheat, (b) spring barley, (c) maize, and (d) winter rye; labelled black circles in (c) refer to Fig. 8.

that the model is a better predictor than the mean value of the observed yields for all crops. Overall model efficiency is reasonable to good for the cereal crops, but less satisfactorily for grain maize. It is worth noting that the spring barley model results were sub-optimally compared with reported country-level yield data since NUTS0 data are only available from EUROSTAT.

An agreement on crop yield averages does not necessarily guarantee sufficient validity throughout the course of the simulated period (Cabelguenne et al., 1990; Niu et al., 2009; Reidsma et al., 2009; Rosenberg et al., 1992). Therefore, we calculated statistical measures for 1997–2007 (Table 2) to assess the spatial performance separately for each year. Furthermore we analyzed the inter-annual yield variability per region (Fig. 5) to address this source of uncertainty. Similarly to overall results, EPIC under-predicted both winter wheat means and standard deviations by 0.2–1.8 t ha^{-1} ($P < 0.05$ for all years) and 0.4–0.5 t ha^{-1} ($P < 0.05$ for five of the 11 years), respectively. The year-to-year overall performance for the other three crops varied between years and crops (see Table 2). The simulated yields were consistent or slightly over-predicted for these crops. The model reproduced about 0.9–1.5 t ha^{-1} lower standard deviations in maize yields compared to reported data.

Both RMSE and Nash–Sutcliffe efficiencies calculated from 1997 to 2007 indicate different model performances between years and crops (Table 2). Year-to-year simulations demonstrate weaker performance compared to the long-term average for maize and rye, and a comparable performance for the other two crops.

The R^2 goodness of fit between simulated and reported yields were 0.64–0.81, 0.73–0.92, 0.29–0.64, and 0.39–0.78 for winter wheat, spring barley, maize and winter rye, respectively. Linear regression slopes were more-or-less consistent with the values in the long-term comparison.

The comparison presented in Fig. 5 demonstrates EPIC's ability to capture inter-annual variability in the regional census yields. Spring barley was not analyzed due to insufficient information in the EUROSTAT database. For winter wheat, the observed yields were significantly related to simulated yields (tested against the r value at $P = 0.05$) in 30% of regions. These are regions of North-Atlantic and Continental Europe, including Denmark, Belgium, Czech Republic, Poland, northern Germany, Hungary and Romania where winter wheat is the dominant crop. Lower correlations were obtained for, with some exceptions, Mediterranean and Boreal regions, and for regions in southwest France, southern Germany and western Austria. The results obtained for winter rye were similar to winter wheat. The highest correlations were calculated for Continental Europe, particularly for some regions in Poland, Hungary, Romania and eastern France. For maize, the temporal variability in simulated yields was significantly related to variability in reported yields in almost 40% of regions. These regions are mainly Germany, France, Hungary, Romania and northern Italy, corresponding to the most important producers of grain maize in EU. Generally, temporal variation was captured less satisfactorily than the spatial patterns in long-term average yields. With our EPIC implementation we were not able to reproduce the entire variability of regional management interventions, technology advances and farm diversity which significantly contribute to deviations in variability over time (Reidsma and Ewert, 2008; Reidsma et al., 2009). This may influence the validation results especially in re-

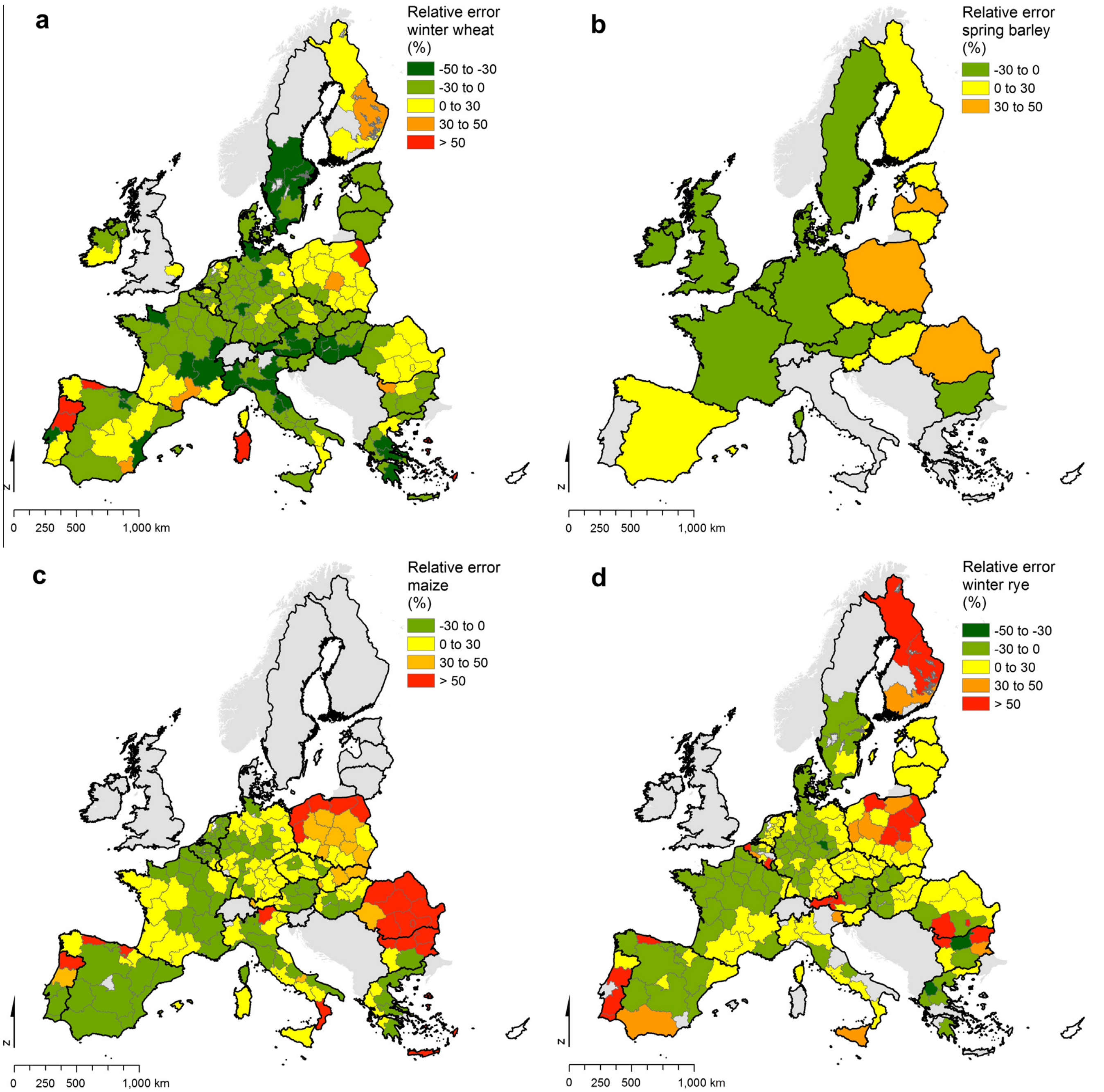

Fig. 4. Relative estimation error (in %) for (a) winter wheat, (b) spring barley, (c) maize, and (d) winter rye.

gions with a relatively modest climatic signal due to high annual rainfall and mild winter and summer temperatures, such as western France. In contrast, the calculations can be negatively influenced by factors not accounted for in the model, such as windstorms, pests, diseases, weeds or freezing of seeds in winter. Uncertainty of the above comparison also depends on quality of regional census data. The EUROSTAT database does not distinguish – *inter alia* – between rainfed and irrigated crop yields and does not capture some important differences in crop varieties, which adds uncertainty to the validation results.

3.2. Crop yield response to meteorological variables

We examined the crop yield responses to principal meteorological variables, including solar radiation, temperature, PET and precipitation. We also examined whether EPIC sufficiently reproduced yield variation in the period 1997–2007 relative to the aridity index (AI), which is a ratio of average annual precipitation and PET. The aridity index was used to quantify the degree of dryness and it identifies dry regions defined by UNEP (1992). We exclusively focused on winter wheat because it is a major European crop, reported continuously and grown under rainfed conditions so that irrigation does not distort the overall picture.

The modelled and reported wheat yields demonstrate similar responses to the driving meteorological variables: they both decrease with increasing solar radiation and PET, increase with growing precipitation and AI, and show an optimum at about 11 °C (Appendix, Fig. 3). The simulated wheat yields exhibit significantly higher variation in dry regions (AI < 0.65; UNEP, 1992) as CVs are exponentially decreasing with increasing AI (Fig. 6a). Similar rela-

Table 2
Year-to-year comparison of simulated and reported annual crop yields and statistical model performance measures.

Year	*m*	Simulated		Reported		Test		RMSE	*E*	Slope	R^2
		Mean	SD	Mean	SD	*t*	*F*				
Winter wheat											
1997	169	4.29	2.04	4.49	2.18	*	ns	1.20	0.69	0.79	0.71
1998	169	4.09	1.67	4.67	2.18	**	**	1.36	0.61	0.63	0.69
1999	202	4.45	2.00	5.01	2.41	**	**	1.25	0.73	0.74	0.79
2000	172	3.85	1.95	4.56	2.31	**	*	1.36	0.65	0.73	0.75
2001	171	4.13	1.99	4.49	2.17	**	ns	1.18	0.70	0.94	0.73
2002	170	3.95	1.90	4.63	2.19	**	ns	1.25	0.67	0.76	0.77
2003	199	4.07	1.87	4.58	2.33	**	**	1.16	0.75	0.72	0.81
2004	157	4.29	1.87	5.37	2.34	**	**	1.71	0.46	0.66	0.68
2005	135	4.00	2.06	4.81	2.34	**	ns	1.37	0.65	0.78	0.78
2006	143	4.00	1.84	4.75	2.16	**	ns	1.34	0.61	0.73	0.73
2007	129	4.17	2.04	4.61	1.98	**	ns	1.35	0.54	0.83	0.64
Spring barley											
1997	20$^+$	4.15	1.12	3.92	1.42	ns	ns	0.59	0.82	0.73	0.86
1998	21$^+$	4.10	0.89	3.78	1.30	*	ns	0.68	0.71	0.62	0.82
1999	22$^+$	4.12	1.08	3.76	1.65	*	ns	0.85	0.73	0.60	0.85
2000	21$^+$	4.09	1.01	3.80	1.61	ns	*	0.80	0.74	0.59	0.87
2001	20$^+$	4.00	1.14	3.82	1.43	ns	ns	0.62	0.80	0.73	0.83
2002	21$^+$	3.99	1.09	3.77	1.30	ns	ns	0.64	0.75	0.74	0.78
2003	22$^+$	3.88	1.08	3.80	1.63	ns	ns	0.67	0.82	0.63	0.91
2004	21$^+$	4.18	0.98	4.35	1.39	ns	ns	0.76	0.69	0.60	0.73
2005	21$^+$	3.87	1.18	3.95	1.43	ns	ns	0.47	0.89	0.79	0.91
2006	21$^+$	3.73	1.17	3.81	1.43	ns	ns	0.44	0.90	0.78	0.92
2007	21$^+$	4.03	1.17	3.81	1.38	*	ns	0.53	0.85	0.80	0.89
maize											
1997	147	7.47	1.64	7.59	2.99	ns	**	2.38	0.36	0.33	0.37
1998	135	7.52	1.57	6.91	2.47	**	**	1.95	0.37	0.42	0.43
1999	181	7.59	1.47	7.55	2.35	ns	**	1.75	0.44	0.42	0.44
2000	150	7.54	1.72	7.42	3.21	ns	**	2.45	0.41	0.35	0.43
2001	149	7.36	1.59	7.40	2.53	ns	**	1.87	0.45	0.43	0.46
2002	147	7.53	1.52	7.45	2.64	ns	**	1.94	0.46	0.40	0.47
2003	177	6.77	1.32	6.74	2.53	ns	**	1.99	0.38	0.33	0.39
2004	135	7.48	1.20	7.64	2.64	ns	**	2.23	0.28	0.25	0.29
2005	125	7.30	1.56	7.91	2.91	**	**	2.51	0.25	0.29	0.29
2006	127	7.64	1.29	7.10	2.45	**	**	2.06	0.28	0.31	0.33
2007	116	7.27	2.07	7.45	3.52	ns	**	2.24	0.59	0.47	0.64
Winter rye											
1997	124	3.48	1.28	3.27	1.58	**	*	0.84	0.72	0.70	0.74
1998	129	3.45	1.24	3.18	1.62	**	**	1.01	0.61	0.61	0.64
1999	163	3.91	1.40	3.74	1.77	*	**	0.87	0.76	0.70	0.78
2000	132	3.46	1.46	3.17	1.58	**	ns	0.87	0.69	0.79	0.73
2001	126	3.26	1.20	3.19	1.50	ns	*	0.92	0.62	0.63	0.62
2002	132	3.45	1.39	3.24	1.59	**	ns	0.81	0.74	0.76	0.76
2003	162	3.43	1.43	3.43	1.67	ns	ns	0.86	0.74	0.74	0.74
2004	124	3.45	1.33	3.77	1.65	**	*	1.09	0.56	0.63	0.60
2005	107	3.18	1.38	3.19	1.51	ns	ns	0.94	0.61	0.73	0.63
2006	115	3.22	1.25	3.23	1.52	ns	*	1.01	0.56	0.61	0.56
2007	105	3.28	1.15	3.09	1.40	ns	*	1.14	0.33	0.51	0.39

Notes: *m* – number of NUTS2/0 regions used in the comparison, two-tailed pair *t*-test and *F*-test (ns – not significant); all R^2 were significant at $P < 0.01$
$^+$ NUTS0 regions.
* Significant at $P < 0.05$.
** Significant at $P < 0.01$.

tionship exists in the reported data, but is less obvious (Fig. 6b). At low AI, the CV values calculated from reported yields were much lower than the CV values of simulated yields for many regions. It indicates that wheat yields reported by individual regions are often more stabilized by management interventions than anticipated by the model.

In addition, since the 11-year period is not sufficient for a comprehensive comparison of crop yields in normal and extreme years, we instead compared simulated against reported yields for the driest and wettest year in this period for each NUTS2 region (Appendix, Fig. 4). We retrieved simulated and reported yield for a year with the highest and the lowest AI value for each NUTS2 region, indicating the wettest and driest year, respectively, and compared them using linear regression. EPIC performed better for the set of driest years, with $R^2 = 0.80$ ($P < 0.01$), compared to the set of wettest years with $R^2 = 0.64$ ($P < 0.01$). This is in agreement with the observations of van der Velde et al. (2012) who found that EPIC, as other crop models, fails to capture the negative impacts of heavy rain and extremely wet conditions.

4. Discussion

Several novel approaches have been used in this study to simulate regional crop yields on a spatial grid. Our simulations especially rely on a spatialization of region-specific crop management and phenology information. Such an approach has been emphasised also by Hutchings et al. (2012) and Leip et al. (2008) and in the CGMS database of the EU JRC (cf. van Ittersum et al., 2003). Future work should expand on comparing our input data and results

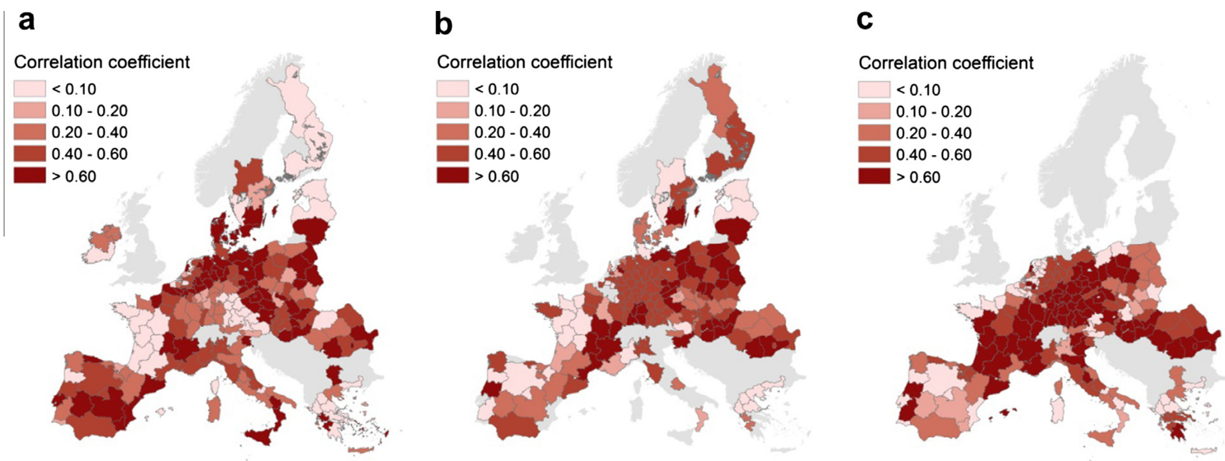

Fig. 5. Correlation between time series of simulated and reported yields calculated for (a) winter wheat, (b) winter rye, and (c) maize; Pearson correlation coefficient $r > 0.60$ is statistically significant at $P < 0.05$.

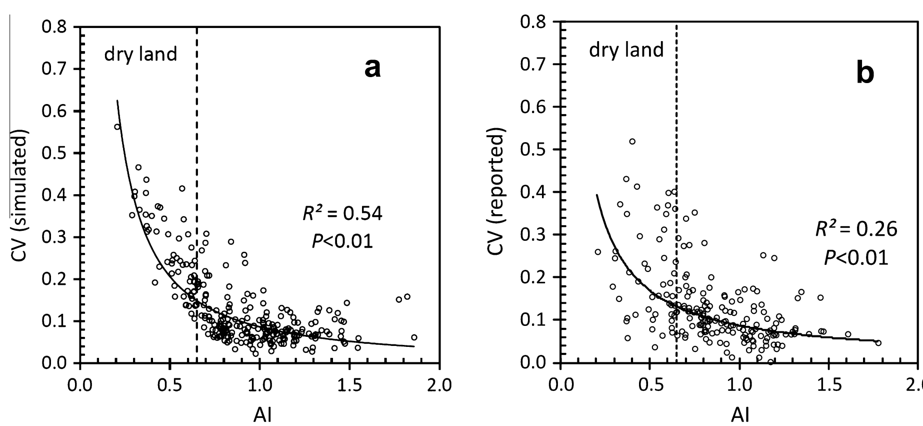

Fig. 6. Relationships between aridity index (AI) and coefficient of variation in winter wheat yields (CV) plotted for (a) simulated and (b) reported yields; vertical dashed line identifies dry lands according to UNEP (1992); the power regression was used.

to comparable large-scale crop model simulations to evaluate uncertainties originating from independent crop phenology and management distributions.

As stated in Section 2.5, only one set of crop model parameters were used for each crop due to the lack of information on crop cultivars, which may lead to a weaker model performance in certain regions (Reidsma et al., 2009). Several studies have implied that crop-growth models can perform better if their crop parameters were subjected to calibration on regional yield statistics (Angulo et al., 2013; Therond et al., 2011; Xiong et al., 2008), but this cannot generally be recommended without further investigation (Angulo et al., 2013) and was not followed in our study.

A common denominator of many European-wide studies is the emphasis on the uncertainties coming from insufficiently captured heterogeneity in crop management (e.g. Boogaard et al., 2013; Supit et al., 2012; Therond et al., 2011; van der Velde et al., 2009, 2012). Since we simulated water- and nutrient-limited regional yields, the impacts of heterogeneity in nutrient and water availability are further investigated to address these sources of uncertainty.

4.1. Crop yield response to PET calculation method

Roloff et al. (1998) emphasised that the performance of the soil water balance component is critical for EPIC's ability to calculate crop yields. Above all, the PET calculation methods determine the EPIC model's accuracy (Benson et al., 1992; Roloff et al., 1998). Therefore, we compared our yields, which were calculated by the H_o PET method, with crop yields simulated by the alternative H_m, PM, PT and BR methods to evaluate their effects on crop yield predictions (Table 3). The H_m and PT methods produced almost 40% higher PET compared to the reference H_o method, which was accompanied by a significant crop yield decrease in all yield intervals (see Table 3). Higher deviations in upper intervals indicate that these two methods generate less stable yields over time in high-productivity regions. The PM method resulted in mean yields that were still significantly lower ($P < 0.01$) in all intervals, but to a lesser extent that the previous two. The PET values generated by the PM method were higher by about 10% on average compared to the reference H_o method. In contrast, the BR method resulted in yields that more-or-less consistent with the reference method, with only minimal differences in means and standard deviations. The BR method slightly under-predicted yields in high-productivity regions compared to our EPIC implementation (based on H_o). Given the yield validation in Fig. 3 and the above results, we conclude that the PM, PT and especially H_m methods lead to strong under-prediction of crop yields reported from highly productive regions (Western Europe). The BR method performs similarly to the reference H_o calculation, and they both allow reproducing near-optimal growing conditions without extensive peaks of water stress. This is also the reason why the H_o method was selected in our EPIC implementation. The yields would decrease significantly if we used the PM, PT or H_m method.

Table 3
Comparison of mean simulated crop yields (t ha^{-1}) with the use of reference (H_o) and alternative PET methods.

Yield interval	n	Ref. PET		Alternative PET															
		H_o		H_m				PM				PT				BR			
						Tests				Tests				Tests				Tests	
		Mean	SD	Mean	SD	t	F	Mean	SD	t	F	Mean	SD	t	F	Mean	SD	t	F
Winter wheat																			
<3	16,165	2.19	0.51	1.55	0.38	**	**	1.76	0.54	**	**	1.66	0.50	**	*	2.30	0.54	**	**
3–5	10,775	4.00	0.60	3.13	0.66	**	**	3.58	0.73	**	**	3.48	0.73	**	**	4.04	0.59	**	ns
5–7	10,865	5.87	0.49	4.65	0.79	**	**	5.36	0.63	**	**	5.27	0.61	**	**	5.84	0.50	**	ns
>7	933	7.58	0.57	6.47	0.91	**	**	7.00	0.75	**	**	7.05	0.62	**	*	7.51	0.55	**	ns
Total	38,738	3.85	1.71	2.98	1.52	**	**	3.40	1.71	**	ns	3.31	1.71	**	ns	3.90	1.65	**	**
Spring barley																			
<3	8605	2.54	0.35	1.78	0.40	**	**	2.25	0.46	**	**	2.02	0.48	**	**	2.75	0.39	**	**
3–4	13,176	3.52	0.29	2.79	0.50	**	**	3.13	0.49	**	**	2.91	0.57	**	**	3.62	0.29	**	ns
4–5	13,355	4.47	0.27	3.71	0.52	**	**	4.17	0.48	**	**	4.04	0.51	**	**	4.49	0.27	**	ns
>5	3602	5.29	0.26	4.66	0.52	**	**	5.05	0.40	**	**	4.97	0.39	**	**	5.29	0.26	*	ns
Total	38,738	3.79	0.91	3.06	1.00	**	**	3.47	1.00	**	**	3.29	1.06	**	**	3.88	0.84	**	**
Maize																			
<4	1979	3.13	0.65	2.18	0.57	**	**	2.16	0.76	**	**	2.51	0.89	**	**	3.50	0.63	**	ns
4–7	11,892	5.88	0.80	4.73	0.92	**	**	4.90	1.12	**	**	5.03	1.04	**	**	6.08	0.78	**	*
7–10	19,346	8.13	0.76	6.96	1.16	**	**	7.23	1.12	**	**	7.43	1.05	**	**	8.20	0.76	**	ns
>10	2896	10.78	0.55	10.57	0.75	**	**	10.59	0.72	**	**	10.60	0.71	**	**	10.80	0.55	**	ns
Total	36,113	7.33	1.88	6.25	2.12	**	**	6.46	2.16	**	**	6.62	2.10	**	**	7.45	1.79	**	**
Winter rye																			
<2	12,887	1.35	0.37	0.99	0.25	**	**	1.11	0.35	**	**	1.04	0.33	**	**	1.39	0.38	**	**
2–4	12,679	2.97	0.61	2.36	0.62	**	**	2.73	0.66	**	**	2.60	0.68	**	**	2.99	0.59	**	**
4–6	12,585	4.81	0.49	3.93	0.64	**	**	4.54	0.57	**	**	4.41	0.57	**	**	4.78	0.50	**	ns
>6	578	6.33	0.23	5.47	0.49	**	**	5.95	0.32	**	**	5.93	0.36	**	**	6.27	0.24	**	ns
Total	38,738	3.08	1.54	2.46	1.36	**	**	2.83	1.54	**	ns	2.72	1.52	**	*	3.09	1.52	**	*

Notes: H_o – original Hargreaves, H_m – modified Hargreaves, PM – Penman–Monteith, PT – Priestly-Taylor, BR – Baier–Robertson; two-tailed paired t-test and F-test (ns – not significant).

* Significant at $P < 0.05$.

** Significant at $P < 0.01$.

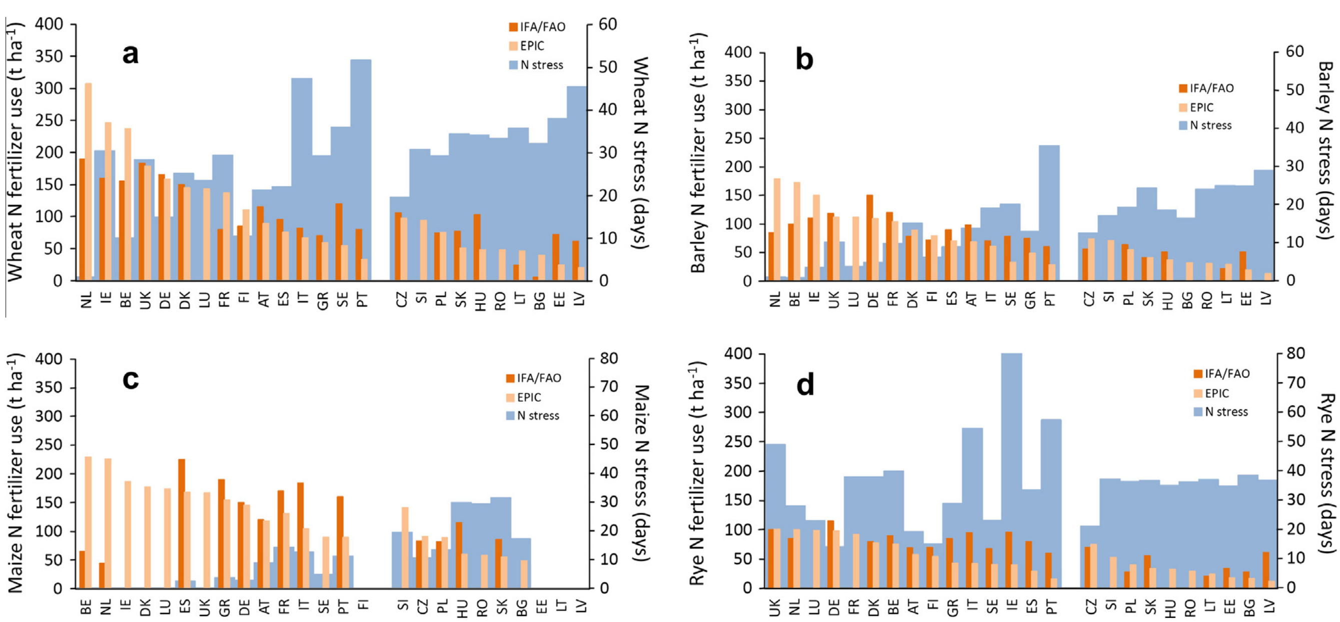

Fig. 7. Comparison of (a) winter wheat, (b) spring barley, (c) maize and (d) winter rye IFA/FAO expert estimates of N-fertiliser application rates and N-fertiliser application rates used in the European EPIC implementation.

4.2. N-fertilizer allocation

Predicting yields is exceptionally sensitive to application rates of supplemental nutrients, and especially nitrogen. In order to express this source of variability, we aggregated our N application rates (see Section 2.4) by countries and compared them with independent national IFA/FAO expert estimates (IFA/IFD/IPI/PPI/FAO, 2002) in Fig. 7. We substantially overestimated the IFA/FAO estimates for winter wheat, spring barley and maize in Netherland, Belgium and Ireland. This is due to excessive use of manure not

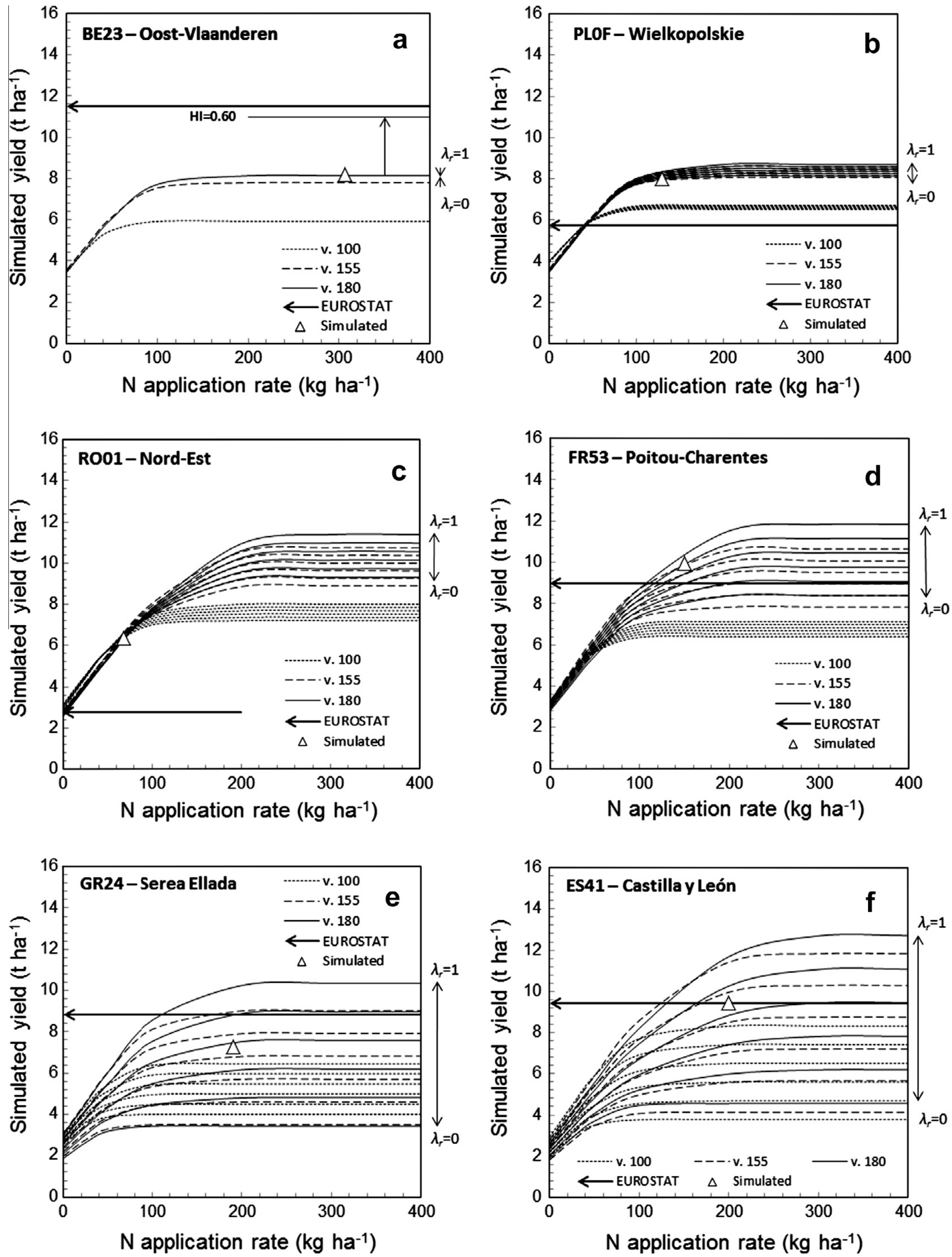

Fig. 8. Relationships between simulated maize yields and N-fertilizer application rates for different maize varieties (v. 100 – early maize, v. 155 – medium-early maize, and v. 180 – late maize) and different irrigation intensities (λ_r from 0 to 1, with 0.2 increments, double-arrow denotes the λ range for v. 180); triangle represents maize yield realizations; horizontal arrow denotes EUROSTAT reported yields.

considered in the IFA/FAO report. In contrast, we moderately underestimated the quantity of N application in many countries for all crops.

Nitrogen stress in Fig. 7 indicates that N deficiency limited achievable yields in many countries. Above all, Eastern European (right group in Fig. 7) and some Mediterranean countries demonstrate substantial N stress due to suboptimal fertilisation rates. The results suggest that the simulated yields could be significantly increased in many regions if more nitrogen was applied. It is also visible that nitrogen did not constrain maize yields in high productive regions of Netherland, Belgium, Germany, and others in Fig. 3 c, since there is almost no N stress for these countries in our simulation.

Several points of criticism can be raised with respect to the approach we have followed here. It is doubtlessly very coarse and respects neither crop rotation particularities nor nutrient stock accumulation. Nevertheless, it enables a spatial distribution of crop yields and nutrient stress.

4.3. Sensitivity to management interventions

Management interventions can significantly contribute to spatial and temporal variability in simulated and reported yields (Reidsma and Ewert, 2008; Reidsma et al., 2009). Therefore, a sensitivity analysis of crop management and cultivar specific characteristics was undertaken to evaluate the model implementation. We demonstrate a range of possible simulation results as determined by changing fertilisation and irrigation intensities and crop cultivars to better understand the uncertainties in the validation in Section 3.1. We focus exclusively on maize. Crop yield responses to changing nitrogen supplies and irrigation intensities are presented in Fig. 8. A total of three maize cultivars with distinct PHUs and vegetation periods were evaluated: (i) early cultivar with a short vegetation period (100 days, dotted curve), (ii) medium-early cultivar with a vegetation period of 155 days (dashed curve), and a late 180-day cultivar (solid curve); all of them with HI = 0.50 and WA = 40. Nitrogen supplies range from 0 to 400 N kg ha^{-1}, covering no to surplus N applications. A total of six water supply strategies with the irrigated area fraction (λ_r) ranging from 0 to 1 (an increment of 0.2) were calculated for all the three cultivars (six lines with respective dash) and six diverse European regions from Belgium (BE23), Poland (PL0F), Romania (RO01), France (FR53), Greece (GR24), and Spain (ES41). In these regions we capture different cases of deviations in simulated versus reported yields from the validation scatterplot in Fig. 3c. The respective yield realizations from Fig. 3c (black circles) are here plotted as triangles lying at a virtual intersection of N-fertilisation, irrigation and cultivar strategies used in our Pan-European EPIC implementation, while horizontal arrows demonstrate reported EUROSTAT yields. The results in Fig. 8 depict uncertainties in simulated yields in different regions since the yield estimates can occur anywhere along plotted lines, or between them, depending on chosen N-fertilisation and irrigation strategy for a given cultivar. It is visible that the irrigation strategy affects yields in Mediterranean regions (ES, GR) much more than in Continental (RO, FR, PL) or Atlantic (BE) regions if requirements for sufficient nitrogen were met, and especially for late maize cultivars. For example, EPIC predicted yields of almost 13 t ha^{-1} on intensively irrigated cropland in ES, whereas only 4 t ha^{-1} on the same land when rainfed. On the other hand, the BE region is almost not sensitive to any irrigation. Nevertheless, during extremely dry or hot conditions, irrigation would also provide relief in these types of regions (van der Velde et al., 2010).

A number of different crop breeds not accounted for in our implementation introduces additional uncertainty. Early cultivars were less sensitive to water deficiency compared to the others as they avoided higher temperatures later in the growing season, but they resulted in lower yields. For instance, Reidsma et al. (2009) reported that insufficiently captured maize breeds can limit model performance in specific regions.

It is worth noting that we used only one combination of the above strategies to reproduce regional yields in this study, while statistical reports mix a number of them. It must necessarily lead to over-simplification and inability to reproduce the entire yield variability. The BE region is a good example of how our "over-simplified" model failed to reproduce reported crop yields. As shown in Fig. 3c, EPIC under-predicted reported crop yield and its variation in the BE region. However, it is noticeable from Fig. 8a that the predicted crop yields cannot be increased whether by applying more N or by additional irrigation. We had to include a more productive late hybrid with HI = 0.6 from Table 1 to approach the reported yields (Fig. 8a). In contrast, the RO region shows much lower reported yields compared to our predictions. This crop yield is consistent with almost no-input subsistence management in our setup (Fig. 8c). We assume that we slightly over-estimated crop technologies in some Eastern European regions and under-estimated them in highly developed Western European countries.

5. Conclusions

The Pan-European EPIC implementation performed effectively in the prediction of regional crop yields for winter wheat, spring barley, maize, and winter rye, while the spatial pattern in average crop yields was reproduced better than inter-annual yield variability. In this study, we benefit from improved calculations of (1) spatially explicit sowing densities, (2) PHUs, (3) crop operation schedule, and (4) nutrient application rates, rather than from "feed-back" calibration of EPIC. We accept the default crop and biophysical process parameter values in EPIC, with only minor adjustments, aiming to evaluate the model in a way by which it is used in most impact studies.

In particular, EPIC was a better predictor for winter wheat, winter rye and spring barley than for maize. We under-predicted yields in highly productive regions of Western Europe and over-predicted those in less productive regions of Eastern Europe. The reproduced crop yields demonstrated narrower variance opposed to the reported yields, indicating that we are not able to account for the entire variability in reported crop yields with our implementation. We showed that our regional model implementation necessarily simplifies effects of crop management options, causing a "flatter" yield reproduction across European regions. The results substantially altered when we used different PET methods, N-fertilizer distribution, irrigation strategy, or crop cultivars. Therefore we expect that the EPIC implementation performance shall increase once we have better regionalization of the above variables.

EPIC performed notably better in dry compared to wet years. The response of simulated yields to relevant meteorological variables was similar to the response observed in reported yields. In contrast to the overall variability statement above, EPIC over-estimated the temporal yield variability for some dry regions (AI < 0.65). The results suggest that farmers in these regions are able to lower water stress and produce more stable yields than anticipated by our EPIC simulations.

We provide a comprehensive and spatially extensive validation of a spatial Pan-European EPIC implementation. Undoubtedly, through an iterative process, these EPIC simulations can be improved by using better Pan-European input data as they become available, as well as using a nested approach for model comparison with reported regional and measured field data. In addition, future work should expand on comprehensive sensitivity and uncertainty analyses to help and identify the most influential model parameters and outline important research and data-gap areas relevant to large-scale crop modelling. We hope that this manuscript will contribute to the availability of harmonised and transparently evaluated agricultural modelling tools in the EU, as well as the establishment of modelling benchmarks as a requirement for sound and ongoing policy evaluations in the agricultural and environmental domains.

Acknowledgements

The research has received funding from the European Community's Seventh Framework Programme (FP7/2007-2013) under grant agreement Nr. 226701 (CARBO-Extreme); Nr. 282746 (IMPACT2C) and FACE MACSUR – Modelling European Agriculture with Climate Change for Food Security, a FACCE JPI knowledge hub (http://www.macsur.eu/) and the Federal Ministry of Agriculture, Forestry, Environment and Water Management of Austria (research Contract No. 100875).

Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.agsy.2013.05.008.

References

Albert, E., 2006. Untersuchungen zur Stickstoff- und Phosphorwirkung von Fleischknochenmehl. KTBL-Schrift 444, Darmstadt.

Angulo, C., Rötter, R., Lock, R., Enders, A., Fronzek, S., Ewert, F., 2013. Implication of crop model calibration strategies for assessing regional impacts of climate change in Europe. Agric. Forest Meteorol. 170, 32–46.

Annoni, A. (Ed.), 2005. European Reference Grids. JRC, Ispra.

Baier, W., Robertson, G.W., 1965. Estimation of latent evaporation from simple weather observations. Can. J. Plant Sci. 45, 276–284.

Balkovič, J., Schmid, E., Moltchanova, E., Skalský, R., Poltárska, K., Müller, B., Bujnovský, R., 2007. Data processing. In: Stolbovoy, V., Montanarella, L., Panagos, P. (Eds.), Carbon Sink Enhancement in Soils of Europe: Data, Modeling, Verification. Office for Official Publications of the European Communities, Luxembourg, pp. 74–139.

Benson, V.W., Potter, K.N., Bogusch, H.C., Goss, D., Williams, J.R., 1992. Nitrogen leaching sensitivity to evapotranspiration and soil water storage estimates in EPIC. J. Soil Water Conserv. 47, 334–337.

Berger, J., 1969. The world's major fibre crops their cultivation and manuring. Centre d'Etude de l'Azote, Zurich.

Billen, N., Röder, C., Gaiser, T., Stahr, K., 2009. Carbon sequestration in soils of SW-Germany as affected by agricultural management – Calibration of the EPIC model for regional simulations. Ecol. Model. 220, 71–80.

Boogaard, H., Wolf, J., Supit, I., Niemeyer, S., van Ittersum, M., 2013. A regional implementation of WOFOST for calculating yield gaps of autumn-sown wheat across the European Union. Field Crop Res. 143, 130–142.

Bouraoui, F., Aloe, A., 2007. European Agrochemicals Geospatial Loss Estimator: Model development and Applications. Office for Official Publications of the European Communities, Luxembourg.

Bouwman, B.A.M., van Keulen, H., van Laar, H.H., Rabbinge, R., 1996. The 'School of de Wit' crop growth simulation models: a pedigree and historical overview. Agric. Syst. 52, 171–198.

BREC, 1990. Blackland Research and Extension Centre, Potential Heat Units Program. <http://swatmodel.tamu.edu/>.

Cabelguenne, M., Jones, C.A., Marty, J.R., Dyke, P.T., Williams, J.R., 1990. Calibration and validation of EPIC for crop rotations in southern France. Agric. Syst. 33, 153–171.

Cabelguenne, M., Debaeke, P., Bouniols, A., 1999. EPICphase, a version of the EPIC model simulating the effects of water and nitrogen stress on biomass and yield, taking account of developmental stages: validation on maize, sunflower, sorghum, soybean and winter wheat. Agric. Syst. 60, 175–196.

CEC, 1985. Soil Map of the European Communities, 1:1,000,000. CEC, Luxembourg.

Challinor, A.J., 2009. Towards the development of adaptation options using climate and crop yield forecasting at seasonal to multi-decadal timescales. Environ. Sci. Policy 12, 453–465.

Danneberg, O.H., 1999. Richtlinien für die Sachgerechte Düngung, fifth ed. Federal Ministry of Agriculture and Forestry, Vienna.

De Geus, J.G., 1973. Fertilizer Guide for the Tropics and Subtropics, second ed. Centre d'Etude de l'Azote, Zurich.

Deng, J., Ran, J., Wang, Z., Fan, Z., Wang, G., Ji, M., Liu, J., Wang, Y., Liu, J., Brown, J.H., 2012. Models and tests of optimal density and maximum yield for crop plants. PNAS 109, 15823–15828.

Ellen, J., 1993. Growth, yield and composition of four winter cereals. I. Biomass, grain yield and yield formation. Neth. J. Agric. Sci. 41, 153–165.

Faivre, R., Leenhardt, D., Voltz, M., Benoit, M., Papy, F., Dedieu, G., Wallach, D., 2004. Spatialising crop models. Agronomie 24, 205–217.

Fleischer, E., 1998. Nutztierhaltung und Nährstoffbilanzen in der Landwirtschaft, Angewandte Umweltforschung, Band 10. Analytica Verlagsgesellschaft, Berlin.

Folberth, C., Gaiser, T., Abbaspour, K., Schullin, R., Yang, H., 2012. Regionalization of a large-scale crop growth model for sub-Saharan Africa: model setup, evaluation, and estimation of maize yields. Agric. Ecosyst. Environ. 151, 21–33.

Galler, J., 1989. Gülle. Leopold Stocker Verlag, Graz.

Goetz, B., 1998. Stickstoffbilanz der österreichischen Landwirtschaft nach den Vorgaben der OECD. Umweltbundesamt, Vienna.

Hansen, J.W., Jones, J.W., 2000. Scaling-up crop models for climate variability applications. Agric. Syst. 65, 43–72.

Hargreaves, G.H., Samani, Z.A., 1985. Reference crop evapotranspiration from temperature. Appl. Eng. Agric. 1, 96–99.

Havlík, P., Schneider, U.A., Schmid, E., Böttcher, H., Fritz, S., Skalský, R., Aoki, K., Cara, S.D., Kindermann, G., Kraxner, F., Leduc, S., McCallum, I., Mosnier, A., Sauer, T., Obersteiner, M., 2011. Global land-use implications of first and second generation biofuel targets. Energy Policy 39, 5690–5702.

Hege, U., Weigelt, H., 1991. Nährstoffbilanzen alternativ bewirtschafteter Betriebe. Bayerisches Landwirtschaftliches Jahrbuch 68, 403–407.

Heumesser, C., Fuss, S., Szolgayova, J., Strauss, F., Schmid, E., 2012. Investment in irrigation systems under precipitation uncertainty. Water Resour. Manage. 26, 3113–3137.

Hutchings, N.J., Reinds, G.J., Leip, A., Wattenbach, M., Bienkowski, J.F., Dalgaard, T., Dragosits, U., Drouet, J.L., Durand, P., Maury, O., de Vries, W., 2012. A model for simulating the timelines of field operations at a European scale for use in complex dynamic models. Biogeosciences 9, 4487–4496.

IFA, IFD, IPI, PPI and FAO, 2002. Fertiliser Use by Crop, fifth ed. FAO, Rome.

Jahn, A., 1991. Gülle- ein wertvoller Wirtschaftsdünger. AID, Bonn.

Jones, C.A., Dyke, P.T., Williams, J.R., Kiniry, J.R., Benson, V.W., Griggs, R.H., 1991. EPIC: an operational model for evaluation of agricultural sustainability. Agric. Syst. 37, 341–350.

Jones, R.J.A., Hiederer, R., Rusco, E., Loveland, P.J., Montanarella, L., 2005. Estimating organic carbon in the soils of Europe for policy support. Eur. J. Soil. Sci. 56, 655–671.

Kaas, T., Fleckseder, H., Brunner, P.H., 1994. Stickstoffbilanz des Kremstales. TU, Vienna.

Kinsel, W.G., 1980. A Field Scale Model for Chemicals, Runoff, and Erosion from Agricultural Management Systems. U.S. Dept. Agric. Conserv. Res. Rept. 26.

Larcher, W., 2003. Physiological Plant Ecology, fourth ed. Berlin, Springer.

Leip, A., Marchi, G., Koeble, R., Kempen, M., Britz, W., Li, C., 2008. Linking an economic model for European agriculture with a mechanistic model to estimate nitrogen and carbon losses from arable soils in Europe. Biogeosciences 5, 73–94.

Leonard, R.A., Knisel, W.G., Still, D.A., 1987. GLEAMS: ground water loading effects on agricultural management systems. Trans. ASAE 30, 1403–1428.

Liu, J., 2009. A GIS-based tool for modelling large-scale crop-water relations. Environ. Modell. Softw. 24, 411–422.

Liu, J., Yang, H., 2010. Spatially explicit assessment of global consumptive water uses in cropland: green and blue water. J. Hydrol. 384, 187–197.

Liu, J., Williams, J.R., Zehnder, A.J.B., Yang, H., 2007. GEPIC – modelling wheat yield and crop water productivity with high resolution on a global scale. Agric. Syst. 94, 478–493.

Liu, J., Folberth, C., Yang, H., Röckström, J., Zehnder, A.J.B., 2013. A global and spatially explicit assessment of climate change impacts on crop production and consumptive water use. PLoS ONE 8 (2), e57750. http://dx.doi.org/10.1371/journal.pone.0057750.

Loehr, L., 1990. Faustzahlen für den Landwirt, seventh ed. Stocker, Graz.

Metzger, M.J., Bunce, R.G.H., Jongman, R.H.G., Mücher, C.A., Watkins, J.W., 2005. A climatic stratification of the environment of Europe. Global Ecol. Biogeogr. 14, 549–563.

Micale, F., Genovese, G., 2004. Methodology of the MARS Crop Yield Forecasting System, vol. 1. Meteorological Data Collection, Processing and Analysis. ISBN 92-894-8130-3–EUR 21291/EN/1.

Monteith, J.L., 1965. Evaporation and environment. Symp. Soc. Exp. Biol. 19, 205–234.

Nash, J.E., Sutcliffe, J.V., 1970. River flow forecasting through conceptual models part I – a discussion of principles. J. Hydrol. 10, 282–290.

Nichols, J., Kang, S., Post, W., Wang, D., Bandaru, V., Manowitz, D., Zhang, X., Izaurralde, R., 2011. HPC-EPIC for high resolution simulations of environmental and sustainability assessment. Comput. Electron. Agric. 79, 112–115.

Niu, X., Easterling, W., Hays, C.J., Jacobs, A., Mearns, L., 2009. Reliability and input-data induced uncertainty of the EPIC model to estimate climate change impact on sorghum yields in the U.S. Great Plains. Agric. Ecosyst. Environ. 129, 268–276.

Parton, W.J., McKeown, B., Kirchner, V., Ojima, D.S., 1992. CENTURY Users Manual. Colorado State University, NREL Publication, Fort Collins.

Petr, J., Lipavský, J., Hradecká, D., 2002. Production process in old and modern spring barley varieties. Die Bodenkultur 53, 19–27.

Priestley, C.H.B., Taylor, R.J., 1972. On the assessment of surface heat flux and evaporation using large scale parameters. Mon. Weath. Rev. 100, 81–92.

Reidsma, P., Ewert, F., 2008. Regional farm diversity can reduce vulnerability of food production to climate change. Ecol. Soc. 13 (1), 38.

Reidsma, P., Ewert, F., Boogaard, H., van Diepen, K., 2009. Regional crop modelling in Europe: the impact of climatic conditions and farm characteristics on maize yields. Agric. Syst. 100, 51–60.

Roloff, G., de Jong, R., Zentner, R.P., Campbell, C.A., Benson, V.W., 1998. Estimating spring wheat yield variability with EPIC. Can. J. Soil. Sci. 78, 541–549.

Rosenberg, N.J., McKenney, M.S., Easterling, W.E., Lemon, K.M., 1992. Validation of EPIC model simulations of crop responses to current climate and CO_2 conditions: comparisons with census, expert judgement and experimental plot data. Agric. Forest Meteorol. 59, 35–51.

Schechtner, G., 1991. Wirtschaftsdünger. BMLFW, Wien.

Schmid, E., Sinabell, F., Liebhard, P., 2004. Effects of reduced tillage systems and cover crops on sugar beet yield and quality, ground water recharge and nitrogen leaching in the Pannonic region Marchfeld, Austria. Pflanzenbauwissenschaften 8, 1–9.

Schmid, E., Balkovič, J., Moltchanova, E., Skalský, R., Poltárska, K., Müller, B., Bujnovský, R., 2006. Biophysical Process Modelling for EU25: Concept, Data, Methods, and Results. Final Research Report for the FP6 Research Project Integrated Sink Enhancement Assessment (INSEA). <http://webarchive.iiasa.ac.at/Research/FOR/INSEA/>.

Schneider, U.A., Havlík, P., Schmid, E., Valin, H., Mosnier, A., Obersteiner, M., Böttcher, H., Skalský, R., Balkovič, J., Sauer, T., Fritz, S., 2011. Impacts of population growth, economic development, and technical change on global food production and consumption. Agric. Syst. 104, 204–215.

Schönhart, M., Schauppenlehner, T., Schmid, E., Muhar, A., 2011. Integration of bio-physical and economic models to analyze management intensity and landscape structure effects at farm and landscape level. Agric. Syst. 104, 122–134.

Sharpley, A.N., Williams, J.R. (Eds.), 1990. EPIC – Erosion/Productivity Impact Calculator: 1. Model Documentation. U.S. Dept. Agric. Tech. Bull. No. 1768.

Siu, D.Z., 1998. GIS-based urban modelling: practices, problems, and prospects. Int. J. Geogr. Inf. Sci. 12, 651–671.
Smith, M., 1991. CROPWAT: Manual and Guidelines. FAO, Rome.
StatSoft Inc., 2003. STATISTICA, Version No. 6. StatSoft, Inc., Tulsa.
Strauss, F., Schmid, E., Moltchanova, E., Formayer, H., Wang, X., 2012. Modelling climatic change and biophysical impacts of crop production in the Austrian Marchfeld region. Clim. Change 111, 641–664.
Stürmer, B., Schmidt, J., Schmid, E., Sinabell, F., 2013. Implications of agricultural bioenergy crop production in a land constrained economy – The example of Austria. Land Use Policy 30, 570–581.
Supit, I., van Diepen, C.A., de Wit, A.J.W., Wolf, J., Kabat, P., Baruth, B., Ludwig, F., 2012. Assessing climate change effects on European crop yields using the Crop Growth Monitoring System and a weather generator. Agric. Forest Meteorol. 164, 96–111.
Tan, G., Shibasaki, R., 2003. Global estimation of crop productivity and the impacts of global warming by GIS and EPIC integration. Ecol. Model. 168, 357–370.
Ten Have, H., 1989. Spezieller Pflanzenbau in den Tropen und Subtropen. Handbuch der Landwirtschaft und Ernährung in den Entwicklungsländern, second ed. Eugen Ulmer Verlag, Stuttgart.
Therond, O., Hengsdijk, H., Casellas, E., Wallach, D., Adam, M., Belhouchette, H., Oomen, R., Russell, G., Ewert, F., Bergez, J.-E., Janssen, S., Wery, J., Van Ittersum, M.K., 2011. Using a cropping system model at regional scale: low-data approaches for crop management information and model calibration. Agric. Ecosyst. Enrivon. 142 (1–2), 85–94.
UNEP, 1992. World Atlas of Desertification. UNEP.
van der Velde, M., Aloe, A., Bouraoui, F., 2009. Pan-European regional-scale modelling of water and N efficiencies of rapeseed cultivation for biodiesel production. Glob. Change Biol. 15, 24–37.
van der Velde, M., Wriedt, G., Bouraoui, F., 2010. Estimating irrigation use and effects on maize yield during the 2003 heatwave in France. Agric. Ecosyst. Environ. 135, 90–97.
van der Velde, M., Tubiello, F.N., Vrieling, A., Bouraoui, F., 2012. Impacts of extreme weather on wheat and maize in France: evaluating regional crop simulations against observed data. Clim. Change 113, 751–765.
van Ittersum, M.K., Leffelaar, P.A., van Keulen, H., Kropff, M.J., Bastiaans, L., Goudriaan, J., 2003. On approaches and applications of the Wageningen crop models. Eur. J. Agron. 18, 201–234.
Wang, X., He, X., Williams, J.R., Izaurralde, R.C., Atwood, J.D., 2005. Sensitivity and uncertainty analyses of crop yields and soil organic carbon simulated with EPIC. Trans. ASAE 48, 1041–1054.
Werner, M., 2001. Shuttle Radar Topography Mission (SRTM), Mission overview. J. Telecom. 55, 75–79.
Wichmann, W., 1999. World Fertilizer Use Manual. IFA, Paris.
Williams, J.R., 1990. The erosion productivity impact calculator (EPIC) model: a case history. Phil. Trans. Roy. Soc. Lond. B 329, 421–428.
Williams, J.R., 1995. The EPIC model. In: Singh, V.P. (Ed.), Computer Models of Watershed Hydrology. Water Resources Publisher, Colorado, pp. 909–1000.
Williams, J.R., Jones, C.A., Dyke, P.T., 1984. A modelling approach to determining the relationship between erosion and soil productivity. Trans. ASAE 27, 129–144.
Williams, J.R., Nicks, A.D., Arnold, J.G., 1985. SWRRB, a simulator for water resources in rural basins. J. ASCE Hydrol. 111, 970–986.
Williams, J.R., Jones, C.A., Kiniry, J.R., Spanel, D.A., 1989. The EPIC crop growth model. Trans. ASAE 32, 497–511.
Williams, J.R., Wang, E., Meinardus, A., Harman, W.L., Siemers, M., Atwood, J.D., 2006. EPIC Users Guide v. 0509. Teaxs AgriLife Research and Extension Center, Temple, TX.
Wösten, J.H.M., Lilly, A., Nemes, A., Le Bas, C., 1999. Development and use of a database of hydraulic properties of Europen soils. Geoderma 90, 169–185.
Wriedt, G., van der Velde, M., Aloe, A., Bouraoui, F., 2009a. Estimating irrigation water requirements in Europe. J. Hydrol. 373, 527–544.
Wriedt, G., van der Velde, M., Aloe, A., Bouraoui, F., 2009b. A European irrigation map for spatially distributed agricultural modelling. Agric. Water Manage. 96, 771–789.
Xiong, W., Holman, I., Conway, D., Lin, E., Li, Y., 2008. A crop model cross calibration for use in regional climate impacts studies. Ecol. Model. 213 (3–4), 365–380.