Regional and global climate projections increase mid-century yield variability and crop productivity in Belgium

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Abstract
The impact of mid-century climatic changes on crop productivity of winter wheat, maize, potato and sugar beet was assessed for a temperate maritime climate in the Flemish Region, Belgium. Climatic projections of multiple regional and global climate models (RCMs from the EU-ENSEMBLES project and GCMs from the Coupled Model Intercomparison Project phase 3) were stochastically downscaled by the LARS-WG weather generator for use in the crop models AquaCrop and Sirius. Primarily positive effects on mean yield were simulated. Crops benefitted from elevated CO_2, and from more radiation interception if the cropping period was adapted in response to higher temperatures. However, increased productivity was linked with increased susceptibility to water stress and greater inter-annual yield variability, particularly with adapted management. Impacts differed among and within ensembles of climate models, and among crops and environments. Although RCMs may be more suitable for local impact assessments than GCMs, inter-ensemble differences and contingent wider ranges of impacts with GCM projections found in this study indicate that applying RCMs driven by a limited number of GCMs alone would not give the full range of possible impacts. Further, this study suggests that the simulated inter-model variation can be larger than spatial variation within the region. These findings advocate the use of both GCM and RCM ensembles in assessments where temperature and precipitation are central, such as for crop production.

Keywords

Climate change; Crop productivity; Global climate model, GCM; Regional climate model, RCM; Multi-model ensemble; Flemish Region, Belgium

Introduction

Crop production is dependent on climate, hence sensitive to climatic changes. In Europe, benefits from climatic changes may subsist in northern latitudes, whereas at lower latitudes afflictions predominate (Ewert et al. 2005; Bindi and Olesen 2011; Himanen et al. 2013). Studies showed northward expansion of suitable growing areas with rising temperature (Maracchi et al. 2005; Fronzek and Carter 2007; Bindi and Olesen 2011). Yet, high temperatures also cause faster accumulation of growing degrees, hence fewer days before thermal requirements for crop development are met. This leads to lower biomass accumulation without cropping management adaptation (Guereña et al. 2001; Audsley et al. 2006). Heat during flowering poses additional threat (Semenov and Shewry 2011; Moriondo et al. 2011). Elevated atmospheric CO_2 concentration ([CO_2]) can increase assimilation rates and improves crop water use efficiency (Vanuytrecht et al. 2012). Altered precipitation may cause water shortage or water-logging (Giannakopoulos et al. 2009). Besides changes in mean climate, altered climate variability also affects yield (Mearns et al. 1997; Porter and Semenov 2005; Moriondo et al. 2011). Because impacts are crop- and region-specific, local assessments provide useful information on upcoming challenges and possible adaptation.

Process-based crop models are appropriate to assess future yield. Projections from global or regional climate models (GCMs and RCMs) can serve as input for local studies after statistical downscaling and/or proper bias correction (Christensen et al. 2008; Ehret et al. 2012; Willems et al. 2012a). RCMs provide dynamically downscaled GCM output, hence represent processes at sub-GCM-grid scales better (Wang et al. 2004; Fowler et al. 2007; Feser et al. 2011). They are assumed more suitable for impact assessments at small scale. Studies for maize and wheat (Mearns et al. 2001) and for maize and soybean (Fronzek and Carter 2007) showed different simulated impacts with RCM versus GCM projections. Still, little is known on whether and how an ensemble of multiple RCMs would affect probabilistic impacts differently from an ensemble of GCMs.

The objective of this study is to assess impacts of downscaled projections of multi-model ensembles of GCMs and RCMs on crop productivity in a temperate climate, including shifted sowing dates and cultivar lengths as adaptation strategy. A case-study is made for key crops (winter wheat, maize, potato and sugar beet) in the Flemish Region, Belgium, being the first simulation study in this region that probabilistically quantifies crop productivity changes considering a multitude of climate projections from RCMs and GCMs, crop responses to elevated [CO_2] and realistic adaptation practices.

Methods

Study area

Climate impacts on crop productivity were assessed in the Flemish Region, Belgium (51.5°-51.7°N, 2.6°-5.9°E). Precipitation is nearly uniformly distributed over the year. In the baseline period, annual rainfall varied between 750 and 850 mm; maximum and minimum monthly temperatures were 23.2 and 1.0°C, respectively. Daily precipitation is typically spatially variable. Yet, with its mostly flat topography and limited size (13 521 km²), the area is considered nearly homogeneous in temperature and reference evapotranspiration (ETo) except for a 30 km-wide strip along the coastline that is influenced by the sea (Baguis et al. 2010). To represent the Flemish Region, one locations in each zone (inland versus coast) was selected: Huldenberg (50.8°N, 4.6°E; 47 m.a.s.l.) and Veurne (51.1°N, 2.6°E; 0 m.a.s.l.).

Key crops in Belgium are winter wheat (*Triticum aestivum* L.), maize (*Zea mays* L.), potato (*Solanum tuberosum* L.) and sugar beet (*Beta vulgaris* L.). Winter wheat is traditionally grown between late October and July/August. Maize, potato and sugar beet are sown in spring (April) and harvested in September-November. Siltloam soils with a high total available water content (TAW, held between field capacity and wilting point) are common. Locally, soils with a lower TAW are present (loamsand inland and clayloam near the coast).

Climate data

Climate data were generated for the baseline (1981-2010) and future (2031-2050) period with the LARS-WG weather generator (Semenov et al. 2010; Semenov and Stratonovitch 2010). LARS-WG was used to downscale GCM and RCM projections because the relatively low resolution of GCM (200-300 km) and even RCM (25-50 km) output causes systematic errors when reproducing small-scale weather patterns for a local study, particularly for precipitation (Christensen et al. 2008; Ehret et al. 2012; Willems et al. 2012a). Various statistical methods exist that correlate coarse climate model output to local climate variables, including regression, weather-typing and stochastic downscaling (Wilby and Wigley 1997; Fowler et al. 2007; Willems et al. 2012b). Online Resource 1 gives fundamentals and justification for use of the stochastic downscaling technique in general and LARS-WG specifically. Local data for the sites representative for distinct zones in the Flemish Region (Huldenberg inland versus Veurne near the coast) were generated based on site parameters characterizing local weather variable distributions. These parameters are available in LARS-WG at 25 km grids across Europe and have been validated for the Flemish Region (Vanuytrecht et al. 2014b).

Each dataset (including precipitation, minimum temperature, maximum temperature, solar radiation, and ETo) consisted of 240 years, a number high enough to ensure adequate risk assessment (Racsko et al. 1991; Semenov et al. 1998). These years are stochastic members of a distribution and thus one by one representative for the whole period (either baseline or future). 240 years of baseline data were generated to exclude potential bias from comparing unequal numbers of observed baseline and generated future data as protruded by the weather generator.

Baseline [CO_2] was assumed 361 $\mu mol \cdot mol^{-1}$ (observed at Mauna Loa Observatory in 1995). Future [CO_2] was assumed 491 $\mu mol \cdot mol^{-1}$ (projected for 2040-A1B; Nakicenovic et al. 2000).

Future climate projections

Multi-model ensembles allow to quantify uncertainty in projections resulting from structural differences in climate models, and facilitate probabilistic projection of climatic changes (Tebaldi and Knutti 2007; Knutti et al. 2010). Two ensembles provided climate projections for 2031-2050: one with 15 GCMs from the Coupled Model Intercomparison Project phase 3 (CMIP3) with resolution 150-400 km (Meehl et al. 2007); one with nine RCMs from the EU-ENSEMBLES project (ENS) with resolution 25 km (van der Linden and Mitchell 2009) (Online Resource 2). As different emission scenarios towards 2050 have small differences in [CO_2] and similar effects on crop yield (Audsley et al. 2006; Olesen et al. 2007), only the A1B forcing emission scenario was envisaged for all climate models. A1B is the global economic scenario that shapes the European Union's energy policy and the only scenario considered in the EU-ENSEMBLES project. The signals extracted from the climate models were the changes in monthly mean variables, except for daily precipitation changes for ENS (Calanca and Semenov 2013). The climate signals were extracted for the grids where the study locations are situated and further downscaled with LARS-WG.

Simulations in this study were limited to the middle of the century for several reasons. The most important was the introduction of more uncertainty when moving further in the future. Also, RCM projections were not generally and readily available until 2100 in the ENSEMBLES project (van der Linden and Mitchell 2009; Calanca and Semenov 2013). Furthermore, near-future predictions are more relevant for the design of adaptation or mitigation measures.

Impact assessment

Crop models

Impacts were simulated with the multi-crop model AquaCrop (Steduto et al. 2009; Raes et al. 2009; Vanuytrecht et al. 2014a) for maize, potato and sugar beet. AquaCrop is a point-based, water-driven model that has been widely used (Stricevic et al. 2011; Abrha et al. 2012; Mkhabela and Bullock 2012; Shrestha et al. 2013; Mhizha et al. 2014) and allows simulation under future conditions, including elevated [CO_2] (Vanuytrecht et al. 2011). Impacts for winter wheat were assessed with the Sirius model (Jamieson et al. 1998) because AquaCrop lacks vernalization and dormancy responses. Sirius is a wheat-specific radiation-driven model. It has been evaluated under a wide range of conditions, including ambient and elevated [CO_2] (Jamieson and Semenov 2000; Jamieson et al. 2000). Online Resource 3 describes key crop responses to climate variables of AquaCrop and Sirius. Complete model descriptions are given by Raes et al. (2009) and Jamieson et al. (1998), respectively.

Model calibration

The models' crop parameters (Online Resource 4) were calibrated for the study area and subsequently validated against independent subsets of field data (including soil water content, crop canopy cover, phenology, biomass and yield throughout the season) collected on farmers' fields between 1999 and 2010 (Vanuytrecht 2013). Calibration included consecutively comparing simulations with observations, updating model parameters and improving the models' performance. Performance was evaluated with the relative root mean square error (rRMSE; Eq.1) and Nash-Sutcliffe coefficient of efficiency (EF; Nash and Sutcliffe 1970; Eq. 2).

$$rRMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(F_i - O_i\right)^2}{n}} \cdot \frac{100}{\bar{O}} \qquad \text{(Eq.1)}$$

$$EF = 1 - \frac{\sum_{i=1}^{n}(O_i - F_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2} \qquad \text{(Eq.2)}$$

with F_i and O_i simulated and observed values; n number of observations; $\bar{O}$ mean value of O_i.

rRMSE is a percentage with values closer to zero indicating better simulation capacity. rRMSE ranges <10%, 10-20%, 20-30% and >30% represent excellent, good, fair and poor performance, respectively (Jamieson et al. 1991). EF is unitless and varies between -∞ and +1 with values closer to unity indicating better simulation efficiency. EF ranges >0.7, 0.35-0.7, 0-0.35 and <0 represent excellent, good, fair and poor performance, respectively.

Impact simulation

Generated baseline and future climate data from individual climate models, and associated [CO_2] served as model input for each location. Additionally, runs with future climate data but baseline [CO_2] were performed. Median impacts were computed for each of the 24 sets of 240 years climate data. These were assembled in boxplots, one for CMIP3 and one for ENS, for evaluation against the median baseline index. A boxplot illustrates the range of predicted impacts associated with the uncertainty in climate change as projected by the multi-model ensemble. The dual representation in boxplots allows comparison of impacts under GCM and RCM projections. The flow from climate projection to impact boxplot is schematized in Online Resource 5.

Water-limited yield (Y; $t{\cdot}ha^{-1}$) and potential yield (Y_{pot}, without water or nutrient stresses; $t{\cdot}ha^{-1}$) were simulated. Inter-annual yield variability was assessed by the coefficient of variation for water-limited yield (CV_y) of 240 runs (Eq.3). Additionally, the length of the growing period (LGP) and a drought stress index (DSI) were determined (Eq.4). The 95-percentile of DSI (DSI_{95}) is the yield lost due to drought stress every 20 years on average.

$$CV_y = \frac{\sigma_y}{\mu_y} \qquad \text{(Eq.3)}$$

with σ standard deviation and μ mean ($t{\cdot}ha^{-1}$).

$$DSI = \frac{Y_{pot} - Y}{Y_{pot}} \quad \text{(Eq.4)}$$

with Y_{pot} potential and Y water-limited yield ($t \cdot ha^{-1}$).

Sensitivity to environmental growing conditions

The sensitivity of impacts to environmental growing conditions was tested at three levels (Table 1): location (inland versus coast), soil (high versus low TAW) and crop management (traditional versus adapted). Adapted management was simulated as altered cultivation timing to make best use of the growing season (in terms of radiation and precipitation), i.e. shifting sowing date and harvest date by growing cultivars with high temperature requirement. For winter crops, sowing is delayed as optimal thermal conditions for sowing occur later. For spring-sown crops, the sowing advancement in response to warming agrees with simulations for mid-latitudes in Europe (Olesen et al. 2012) and with observed trends (Kaukoranta and Hakala 2008; Sacks and Kucharik 2011; Olesen et al. 2011).

Statistics

Statistical tests were performed to compare baseline versus future climate and impacts: null hypotheses for equal distributions of two-sample Kolmogorov-Smirnov (KS) tests and for equal means of unpaired t-tests (if data were normally distributed) or Mann–Whitney U-tests (if normality was violated) were tested at the 5% threshold probability level for 240 data. For the multi-model ensembles, the distribution and mean of 240 climatic data or simulations of the ensemble median (model) were subjected to the tests.

Results and discussion

Model performance

There was good agreement between simulated and observed yield for four crops at the validation fields, after calibration of crop parameters against independent data (Fig.1). Statistical indices (rRMSE < 10% for wheat and maize and < 15% for potato and sugar beet, and positive EF values; Table 2) support the good performance of both crop models.

Baseline production

Median simulated dry yield of winter wheat, maize, potato and sugar beet averaged over all environmental conditions was 9.7, 10.8, 13.9, 14.3 $t \cdot ha^{-1}$, respectively. Simulated values correspond well with national statistics for the baseline period (8.9, 11.2, 11.1, 12.6 t•ha-1 and 9.5, 11.9, 12.8, 13.9 t•ha-1 for mean and maximum dry yields over the past six years, respectively; FOD Economie 2014) considering that national yields account for infestations whereas the models do not.

Simulated wheat and sugar beet yields were higher near the coast than inland, whereas maize and potato yields were lower and more variable (Fig.2). Near the coast, thermal mitigation can occur. This is a temperature moderating effect that raises low winter temperatures and reduces high summer temperatures, thus reducing cold stress in winter, and delaying maturity and increasing potential radiation interception in summer. The effect exerted a net positive result on wheat and sugar beet yields, whereas delayed maturity subjected maize and potato to drought stress at the end of the growing cycle. Drought stress was no limitation for wheat (DSI = 0).

For the spring-sown crops conversely, the risk of yield loss due to water stress was high on low-TAW soils resulting in lower mean and more variable yields.

Climate projection

CMIP3 projects inland precipitation will increase in the winter months and decrease in July and September (Online Resource 6). There is no such decrease in summer precipitation near the coast. ENS projects increases in precipitation in winter near the coast, but not inland. Summer precipitation does not decrease. These findings agree with the tendency of high-resolution scenarios (from RCMs) towards precipitation increase or stability instead of decrease, particularly in summer (Christensen and Christensen 2007). Inter-model and spatial (i.e. difference between the coastal and inland area) variation in projections were generally not larger for ENS than for CMIP3. Besides the presented (modest) differences in monthly totals, shifts in rainfall distribution were present, which potentially affect crop production.

All models agree on future temperature rises. CMIP3 projects larger median temperature increases in summer and early autumn, but smaller increases in winter than ENS. Remarkably, CMIP3 projects larger temperature increases in summer than in winter, whilst the opposite is true for ENS. Inter-model variation is similar for both ensembles. Spatial variation is limited.

Associating RCMs with their parental GCM showed that RCMs project mostly stronger warming in winter and reduced or equal warming in summer. RCM precipitation projections can divert significantly from projections of the parental GCM, sometimes even projecting the opposite effect. There were no general unambiguous indication of dominance of the parental GCM in the climate signals of nested RCMs. Close resemblance was only detected between SMHIRCA-BCM and the parental BCM. For the other model families, RCM signals could divert individually and largely from the parental GCM signal. This study did not endorse the dominance of the driving GCM in the RCM-signal, or less pronounced temperature and precipitation changes for RCMs compared to their driving GCM, as was mentioned by other studies (Olesen et al. 2007; Christensen and Christensen 2007; Fronzek and Carter 2007). It has to be noted however that these studies compared GCMs and RCMs over large regions and several grids, while this study compared GCM and RCM output grid by grid. Unfortunately, no exhaustive comparison within or between model families was possible because the available RCMs from ENS do not allow a systematic survey. The same problem of no comparably large sets of RCM runs by different driving models was mentioned in earlier studies.

Future production

Simulated yield impacts are visualized in Fig.2. The significance of difference in mean yield (of 240 simulations) between the ensemble median and the baseline, or between two ensemble medians is presented in Online Resource 7.

Wheat

Wheat yield increased by 11 to 14% notwithstanding a shorter LGP (minus 10 days to two weeks) due to faster accumulation of thermal time following temperature increase. There were no differences between high- and low-TAW soils because production was not water-limited. Trends were similar among the two locations, but yield increase was slightly larger near the coast. For winter wheat, delaying sowing was an appropriate management adaption since higher temperatures delay favourable sowing conditions for winter cereals. Late sowing caused further decrease of LGP. Yields were higher than the baseline but slightly lower compared to yields if the traditional sowing date was used. Rather than drought stress, shorter LGP is the main factor affecting future winter wheat production. Shorter LGP helps to avoid water stress (DSI remained zero), but it also reduces the potential amount of intercepted radiation. That unfavourable effect is counterbalanced by a positive CO_2 effect on biomass production and crop transpiration (illustrated by the no-CO_2 scenarios) that is common for all C3 crops (e.g. Vanuytrecht et al. 2012). Higher temperatures also reduce frost and overwintering damage. Previous impact assessments in Europe already mentioned increasing wheat yields (Eckersten et al. 2001; Torriani et al. 2007; Olesen et al. 2011). Others described increased vulnerability due to heat stress during flowering (Gobin 2010; Semenov and Shewry 2011; Supit et al. 2012). But this effect is not expected to reduce wheat yields before 2050 in the Flemish Region.

Maize

Inland future maize yield differed from the baseline, with the direction of change dependent on the ensemble. Under ENS projections yield increased by 3% with an associated LGP decrease by two weeks. Under CMIP3 projections yield decreased by 2 to 3% associated with an LGP decrease of over three weeks. No change in DSI_{95} was simulated. Near the coast, mean yield increased under both ensemble projections, although less under CMIP3 (5%) than under ENS (8-9%) projections. Adapting management caused increases of 16 to 17% depending on ensemble, location and soil. Notwithstanding mean yield increases, DSI_{95} and inter-annual yield variability simultaneously increased, particularly on low-TAW soils. Without management adaptation, yield increases were smaller than for C3 crops, because maize shows a lower production response to elevated [CO_2] (evidenced by the no-CO_2 scenarios). Due to its C4 photosynthetic pathway, CO_2 benefits maize growth mainly due to improved water use efficiency (Vanuytrecht et al. 2012). Simulated differences between ensembles are explained by higher CMIP3 temperature projections throughout the maize growing season as compared to ENS, and the resulting shorter LGP (over three weeks under CMIP3 vs. two to three weeks under ENS compared to the baseline). Because cumulative biomass production is proportional to intercepted radiation, acceleration of crop development and shortening of LGP reduces potential yield, even though crops benefit from cold stress and frost damage reduction due to the temperature increase. The results confirm that maize, which thrives in tropical conditions, will not suffer from temperature extremes in Western Europe (Supit et al. 2010). Yet, for low-TAW soils and late maturing cultivars, drought and increased climate variability challenges maize yield (Olesen et al. 2011).

Potato

Potato yield increased by 16 to 26% depending on the ensemble and environmental conditions. The increase was significantly different from the baseline except near the coast on a low-TAW soil. Yield increased notwithstanding a shorter LGP by approximately one week (ENS) to almost two weeks (CMIP3). Under CMIP3 projections – with lower summer precipitation and higher temperatures – drought stress risk (DSI_{95}) increased, while DSI_{95} decreased under ENS projections. Adapting management boosted yield further and LGP increased up to one week compared to the baseline. The only exception was found inland under CMIP3 projections and with a low-TAW soil, due to late drought stress that forced a faster ending of the growing cycle. DSI_{95} increased under CMIP3 projections whereas under ENS projections, DSI_{95} remained mostly stable. For potato, higher temperatures and a shorter LGP alone would reduce potential yield. Yet, potato benefits maximally from the CO_2 fertilization effect (illustrated by the no-CO_2 scenarios). Still, with its superficial root system, the crop is susceptible to drought risk and high inter-annual yield variability. The results correspond with simulated impacts in the UK and Western Europe where the fundamental challenges for future potato cultivation are not super-optimal temperatures but increased drought stress and irrigation needs (Holden et al. 2003; Supit et al. 2012; Daccache et al. 2012).

Sugar beet

Beet yield increased between 6 to 13%, notwithstanding shortening of LGP by almost three to five weeks. DSI_{95} often did not increase. Yield increases were larger inland than near the coast. The risk of yield failure due to drought stress (DSI_{95}) did not increase except on a low-TAW soil near the coast. Adapting management was beneficial with yield increases varying between 12 and 20%, depending on location, soil type and ensemble. Higher temperatures and a shorter LGP alone would reduce potential yield but similar to potato, sugar beet benefits substantially from the CO_2 fertilization effect (illustrated by the no-CO_2 scenarios). The simulated positive trends for sugar beet yield are in agreement with simulated impacts in the UK (Richter et al. 2006).

Yield variation

As well as changes in mean yield, changes in inter-annual yield variability are of interest. There are caused by drought stress and already indicated by simulated changes in DSI_{95}. Fig.3 illustrates the inter-annual yield variability inland on a high-TAW soil for the baseline and future period under traditional and adapted management. With traditional management, CV_y increases were not universal (Table 3). If there was an increase in CV_y, it was mainly due to an increase in mean yield rather than to a reduction in variation. Although adapted management increased mean yield, it also increased inter-annual variation and CV_y for maize and potato and under particular conditions for sugar beet. Projected precipitation in August was a major factor affecting inter-annual yield variability. The highest inter-annual yield variability in the baseline and future was simulated for potato, which is susceptible to drought stress with its superficial roots. Our results showed higher yields under future climate conditions, and particularly with adapted management, but at a cost of lower inter-annual yield stability. Generally, farmers are more likely to be risk-averse than risk-neutral, and prefer stable yields (Bontems and Thomas 2006; Serra et al. 2006; Groom et al. 2008; Knoke et al. 2011). Yet, even more important than stable yields is stable income. An economical evaluation building further on this study would be interesting to assess whether yield instability comes with income instability.

Variation in simulated yield existed also between climate models and climate model ensembles. Inter-ensemble variation was small for wheat and sugar beet, but could be large - and larger than inter-model (or intra-ensemble) variation - for maize and potato. The finding that inter-ensemble variation was more important for maize and potato can be associated with the importance of precipitation. Precipitation affects crops limited by water stress more and is likely to differ between climate models with different resolution. Differences between CMIP3 and ENS ensembles are partially associated with incorporated sub-GCM-grid processes in RCMs (Olesen et al. 2007). Earlier studies in the US for maize and wheat (Mearns et al. 2001) and in Europe for maize and soybean (Fronzek and Carter 2007) demonstrated that differences between RCM and GCM projections can affect simulated yield impacts of climate change, depending on the crop and conditions simulated. This is supported by the present study. Although RCMs resolve sub-GCM-grid processes better (Feser et al. 2011) and may be more suitable for agricultural assessments at small scale, RCM-based projections and predicted impacts are suspected to follow those from the driving GCM (Christensen and Christensen 2007; Fronzek and Carter 2007). This implies that using RCM-based scenarios driven by a limited number of GCMs alone may not provide a representative range of impacts. Although the dominance of the parental GCM signal could not be unequivocally detected in this study, wider ranges of predicted impacts under CMIP3 projections (e.g. for potato and maize) suggest that by applying ENS alone, a representative range of impacts would not be assessed. Therefore, using both GCM- and RCM-based scenarios is advised.

The degree of spatial variation in modelled impacts (i.e. difference between the inland and coastal region) differed among crops. Except for maize, inter-model variation was larger than spatial variation. This was also true for ENS projections, which may be expected to reproduce local weather phenomena and introduce more spatial variation in yield impacts (Fronzek and Carter 2007). This finding advocates the use of multiple climate models in crop production assessments. It contrasts with the conclusion of Olesen et al (2007) who, unlike this study, assessed multiple climate model grids and concluded that impact variation associated with environmental conditions may be more important than the variation due to projected climate change in Europe.

Considerations and directions for further research

Positive impacts on mean crop yield were simulated in the Flemish Region, especially with adapted management. Crops benefitted from elevated [CO_2] and increased radiation interception if cultivars with higher temperature requirements were grown. Although altering the cropping period improved average yield, it also increased risk including increases in water requirements of crops with longer LGP, susceptibility to water stress, inter-annual yield variability, and pressure on water resources. Adopting adaptation measures therefore requires evaluation of the trade-off between benefits of late maturing cultivars in normal and wet years and potential losses in dry years. But failure to consider adaptation may underestimate potential beneficial effects of climatic changes on crop productivity (Olesen et al. 2012).

Potential bias in coarse-scale GCM and RCM output necessitated downscaling (and bias correction) of the outputs for this local impact study (Themessl et al. 2011; Ehret et al. 2012; Willems et al. 2012a). However, statistical downscaling has drawbacks, particularly in relation to underestimation of inter-annual variation, such as overdispersion (i.e. underrepresentation of successive days with large (or small) temperature or precipitation sums; Wilks and Wilby 1999; Kim et al. 2012); elimination of inter-annual variation in climate output by applying a single change factor (Kendon et al. 2008; Prudhomme et al. 2010); events outside those present in the selected series of baseline weather that cannot be reproduced (Wilby and Wigley 1997; Wilby et al. 1998; Fowler et al. 2007); and unanticipated effects to secondary variables when modifying precipitation distributions by climate change factors (Wilby and Wigley 1997; Willems et al. 2012b). In particular, LARS-WG performs well for the generation of mean monthly weather variables but may understate the variance in observed precipitation data (Sunyer et al. 2012; Taye and Willems 2013). Different downscaling methods should therefore be used to map the uncertainty arising from the downscaling method (Chen et al. 2011; Taye and Willems 2013). This is particularly important during prolonged periods of extreme conditions, because this may result in a series of low yields, which will have long-term implications for farming systems.

Simulated changes in crop productivity in this study were dependent on crop responses to elevated [CO_2]. The simulated responses of different crops were developed in a study on the AquaCrop model (Vanuytrecht et al. 2011) using crop responses to CO_2 measured in free air CO_2 enrichment (FACE) environments (Vanuytrecht et al. 2012). However, while FACE studies indicate that field crops respond positively to elevated [CO_2], actual responses depend on the crop's sink strength, which is affected by internal (genetic) and external (e.g. adequate nitrogen availability) factors (Poorter 1993; Leakey et al. 2009; Vanuytrecht et al. 2011). Crop responsiveness may diminish over time through photosynthetic “acclimation” whereby the maximum carboxylation rate decreases (Stitt and Krapp 1999; Ainsworth and Rogers 2007). The no-CO_2 simulations in this study therefore demonstrate not only the contribution of elevated [CO_2] to the total climate change impact but also the consequences for yield if the CO_2 fertilization effect does not occur due to inadequate management or acclimation. Without CO_2 effect, simulated yields for wheat, and especially potato and sugar beet are lower under all conditions, even with management adaptation. Yet, the water saving effect of transpiration reduction at elevated [CO_2], which is universal and independent of sink strength or acclimation effects (Leakey et al. 2009), is also eliminated in the no-CO_2 simulations. Therefore, these simulations are unrepresentative for maize because it is a C4 crop that predominantly benefits from elevated [CO_2] through water saving effects. A further consideration regarding the representativeness of simulated crop responses to elevated [CO_2] includes grain and fodder quality since these can decrease following altered carbon-nitrogen ratios and decreased protein contents (Taub et al. 2008; Leakey et al. 2009; Kant et al. 2012). A follow-up study that simulates grain and fodder quality could quantify the implications for the region.

In addition to the model parameterization of crop responses to elevated [CO_2], simulated impacts were also affected by the model used. Uncertainty in predictions due to crop model, which are likely to affect the magnitude of simulated impacts (Asseng et al. 2013), was not considered. However, variation in simulated impact among different crop models is smaller in high-yielding environments, for lower climatic changes (early- to mid-century projections, or low to moderate emission scenarios) and for well calibrated models (Asseng et al. 2013). These conditions apply to this study. Further, Olesen et al (2007) emphasized the general agreement on direction of change among studies in Europe made with different models. Thus while the magnitude of simulated impacts in this study may have been different if other impact models had been used, the trend of changes in simulated productivity would probably not be conditioned on the impact model. Trends in productivity predicted in our study were consistent with other studies for mid to high latitudes in Europe (Olesen and Bindi 2002; Audsley et al. 2006; Olesen et al. 2011; Bindi and Olesen 2011; Supit et al. 2012).

Predicted crop productivity in our study may be overstated because the effect of changed climates on other factors such as pests and nutrient management were not included. Temperature rises may provide conditions that promote crop diseases and survival of crop pests (Olesen et al. 2011). In addition, productivity increases and longer LGP may increase crop nutritional requirements but at the same time result in increased nutrient leaching. Future management need to be adapted to fulfil the predicted positive impacts of climatic changes (Olesen et al. 2011; Bindi and Olesen 2011).

Mid-century temperature projections used in this study are moderate and not high enough to reduce assimilation substantially in the study region (Supit et al. 2010), leading to mainly positive impacts. End-of-the-century projections include higher temperatures and more frequent and extreme periods of drought. These stronger climatic signals are expected to cause more negative impacts on mean yield and deteriorate stability further (IPCC 2013; IPCC 2014).

A follow-up analysis to this study that involves an economic and/or a GIS model to incorporate price effects and influences of agricultural policy measures on cultivated area would add value for an integrated, regional assessment.

Conclusions

Mid-century climatic changes are predicted to increase yield variability and crop productivity in the Flemish Region, especially with adapted management. Average crop yields increased in response to both elevated [CO_2] and more radiation interception if the cropping period was adapted for higher temperatures. However, increased productivity was linked with increased susceptibility to water stress and greater inter-annual yield variability.

Impacts differed among and within ensembles of climate models with different resolution, among crops and environments. Impacts for spring-sown crops were generally more positive under the lower summer temperatures projected by the RCMs of ENS. The RCMs resolve sub-GCM-grid processes better and may be more suitable for local impact assessments. Despite this, inter-ensemble differences and contingent wider ranges of predicted impacts with the GCM projections of CMIP3 indicate that the full range of possible impacts is not assessed when applying RCMs driven by a limited number of GCMs alone. Further, this study suggests that the simulated inter-model variation can be larger than spatial variation within the region. Accordingly, both GCM and RCM ensembles should be used in assessments where temperature and precipitation are central, such as for crop production.

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Figures

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Fig. 1 Observed versus simulated baseline yield of validation fields with winter wheat (circles), maize (diamonds), potato (squares) and sugar beet (stars) in the temperate maritime climate of Belgium

Fig. 2 Simulated baseline yield (Y; black with standard deviation in bottom graphs) and future change (boxplots in top graphs; hatched for CMIP3 projections, open for ENS projections) for the four crops inland (left panel) and near the coast (right panel) for traditional (TM) and adapted (AM) management on soils with a high and a low totally available water content (TAW). Grey boxplots represent no-CO_2 scenarios.

Boxplots illustrate uncertainty in simulated yield due to climate model-inherent differences between members of a multi-model ensemble. Box boundaries represent 25- and 75-percentiles, thick line within the box represents the median, whiskers represent 10- and 90-percentiles. The dashed horizontal line reflects no change from the baseline to the future. * shows significant difference in mean yield (of 240 simulations) between the ensemble median and the baseline at threshold probability value $p < 0.05$ (only for scenarios with consideration of CO_2).

Fig. 3 Cumulative probability distribution of 240 simulated yields in the baseline period (black) and the future (grey) under climatic changes projected by individual models of the CMIP3 ensemble (full) and the ENS ensemble (dashed) for the four crops with traditional (left column) and adapted (right column) management (data shown for a high-TAW soil (siltloam) inland). Projections of the climate model that represents the median of each ensemble is indicated in red.

Figure 1
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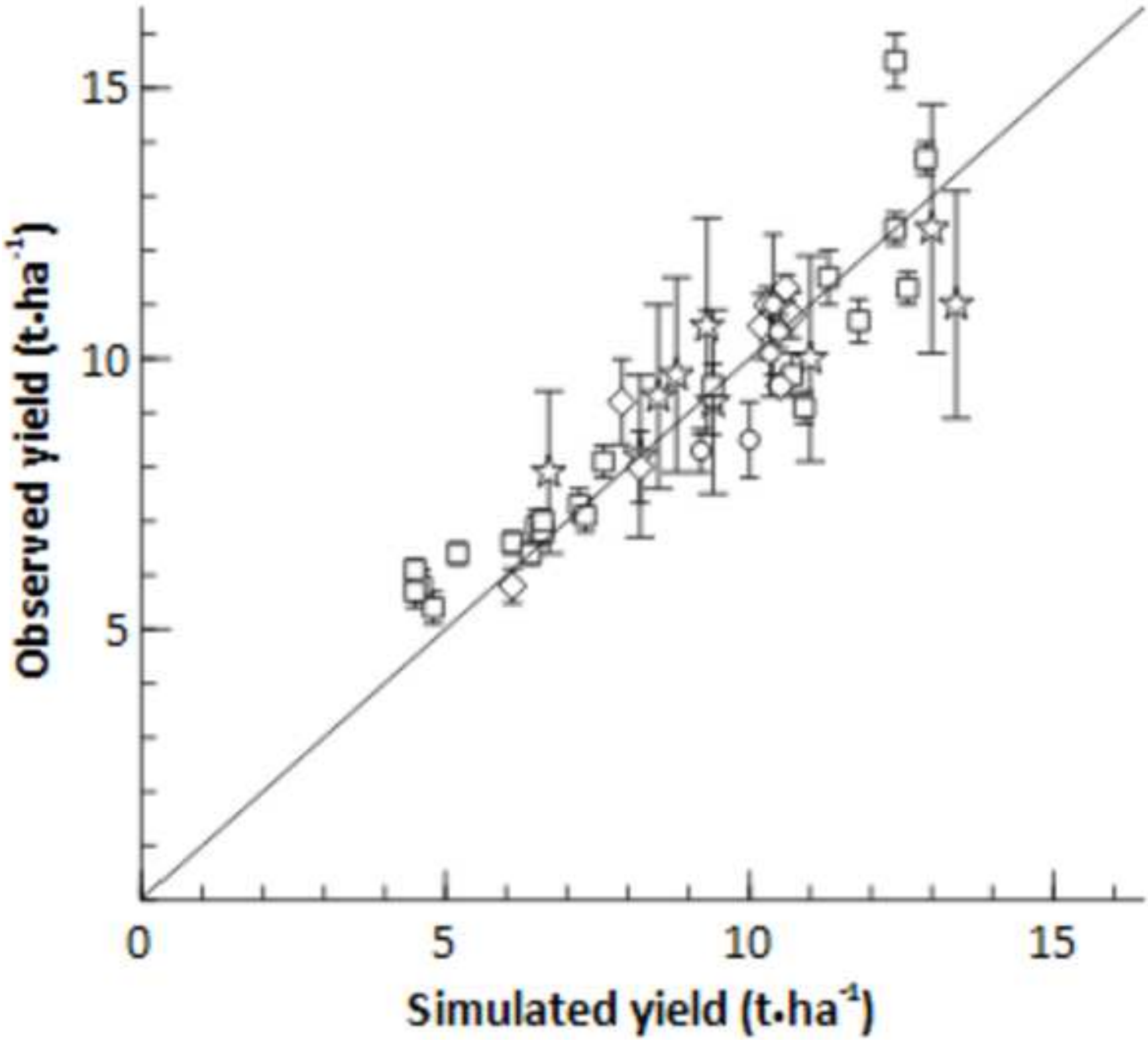

Figure 2

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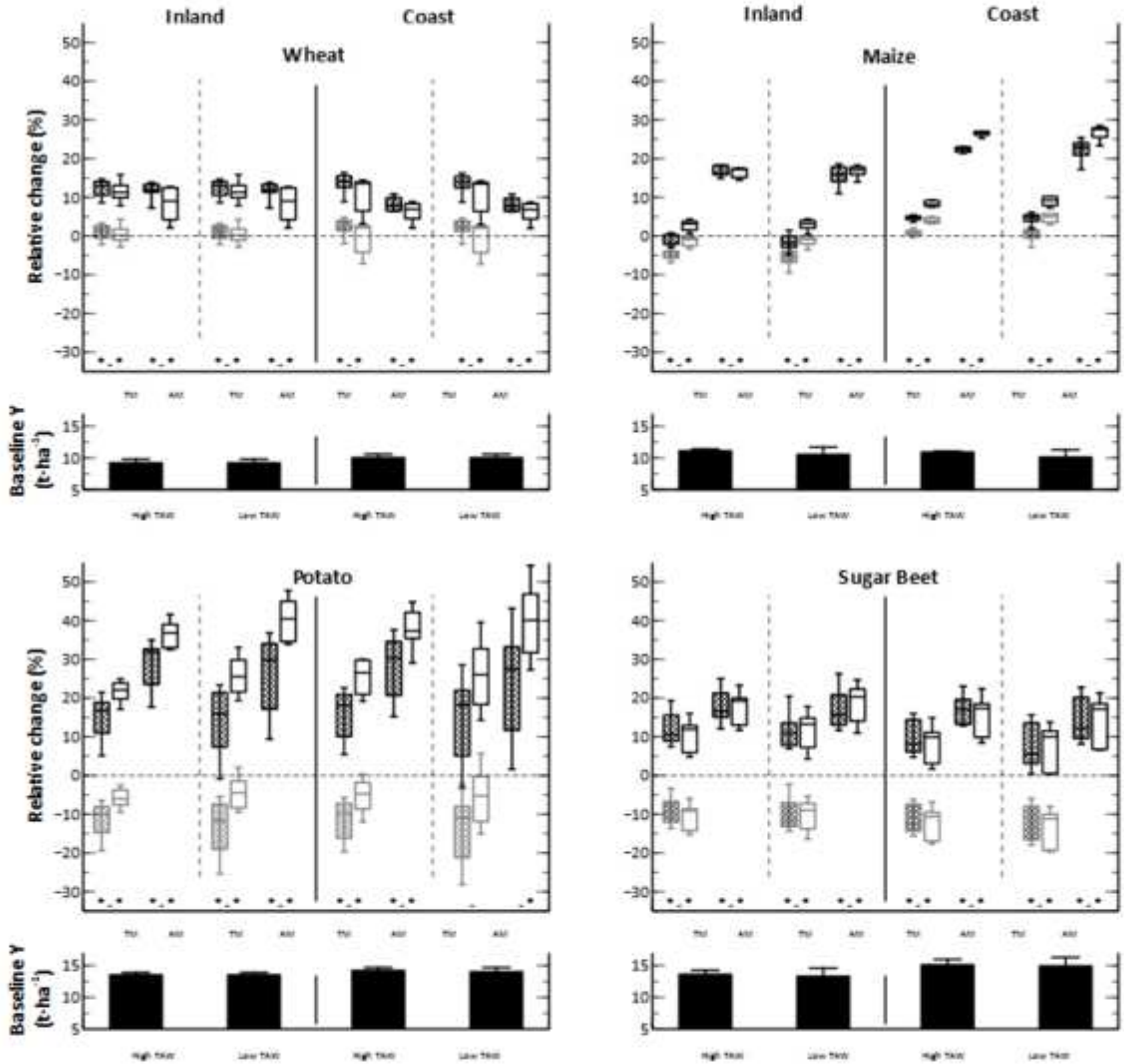

Figure 3
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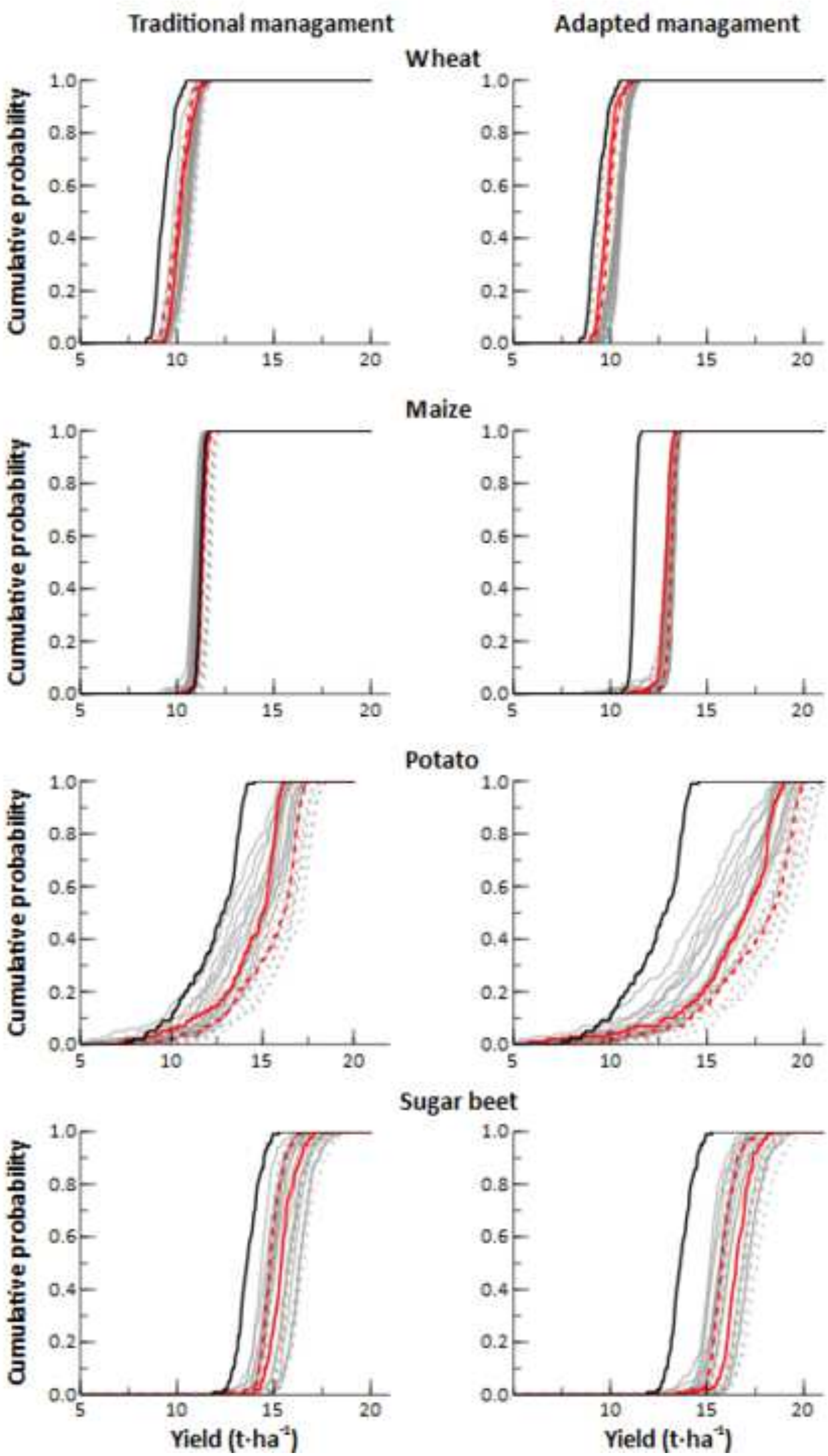

Table 1

Table 1 Growing conditions considered for the impact assessment

Location								
	Inland				**Coast**			
Tmax (°C)	23.2				21.6			
Tmin (°C)	1.0				1.7			
Annual *P* (mm)	795				786			
Soil								
	High TAW				**Low TAW**			
Type	Siltloam (inland & coast)				Loamsand (inland)		Clayloam (coast)	
TAW ($mm \cdot m^{-1}$)	223				173		184	
Management								
	Traditional				**Adapted**			
Crop	Winter wheat (*tb* 2°C)	Maize (*tb* 8°C)	Potato (*tb* 2°C)	Sugar beet (*tb* 5°C)	Winter wheat (*tb* 2°C)	Maize (*tb* 8°C)	Potato (*tb* 2°C)	Sugar beet (*tb* 5°C)
Sowing date	25 Oct	25 Apr	25 Apr	25 Apr	15 Nov	4 Apr	4 Apr	4 Apr
Thermal requirement (GDD)	1900	1200	1850	1850	1900	1350	2050	1950

Tmax: mean monthly maximum temperature; **Tmin**: mean monthly minimum temperature; ***P***: annual precipitation; **TAW**: totally available water content; **tb**: crop base temperature

Table 2

Table 2 Statistical indices for model validation based on final dry yield simulation in the baseline period

Model	Crop	*n*	Observations range ($t{\cdot}ha^{-1}$)	Simulations range ($t{\cdot}ha^{-1}$)	rRMSE (%)	EF
AquaCrop	Maize	8	5.8 – 11.3	6.1 – 10.7	7.3	0.70
AquaCrop	Potato	22	5.4 – 15.5	4.5 – 12.9	12.6	0.85
AquaCrop	Sugar beet	9	7.8 – 12.4	6.6 – 12.9	11.5	0.27
Sirius	Winter wheat	5	8.3 – 11.0	9.2 - 10.5	7.1	0.42

n: number of independent experiments used for validation; **rRMSE**: relative root mean square error; **EF**: model efficiency

Table 3

Table 3 Coefficient of variation for yield (CV_y) under baseline conditions and under the median climate model from the CMIP3 and ENS ensembles

	Winter wheat			Maize			Potato			Sugar beet		
	Baseline	CMIP3	ENS	Baseline	CMIP3	ENS	Baseline	CMIP3	ENS	Baseline	CMIP3	ENS
Traditional sowing date and cultivar												
Soil with high totally available water content (TAW)												
inland	0.049	0.048	**0.051**	0.021	0.019	0.020	0.133	**0.140**	0.123	0.046	0.044	0.040
coast	0.048	0.045	0.044	0.036	0.031	0.030	0.202	0.189	0.176	0.053	0.053	0.048
Soil with low TAW												
inland	0.049	0.048	**0.051**	0.108	0.105	0.099	0.262	**0.272**	0.243	0.089	0.089	0.077
coast	0.048	0.045	0.044	0.109	**0.116**	0.108	0.371	0.352	0.328	0.083	**0.087**	0.080
Adapted managment[a]												
Soil with high TAW												
inland		0.041	0.043		**0.026**	**0.024**		**0.165**	**0.140**		0.045	0.042
coast		0.045	0.046		**0.049**	**0.055**		**0.226**	**0.215**		**0.058**	0.051
Soil with low TAW												
inland		0.041	0.043		**0.165**	**0.109**		**0.291**	**0.278**		**0.090**	0.083
coast		0.045	0.046		**0.165**	**0.176**		**0.417**	**0.372**		**0.096**	**0.088**

[a] Early sowing date and late-maturing cultivar for maize, potato and sugar beet; late sowing date and traditional cultivar for wheat

Supplementary material 1. Fundamentals of the stochastic downscaling technique and the LARS-WG weather generator

LARS-WG belongs to the group of stochastic weather generators (WGs). Like other WGs, LARS-WG generates synthetic time series of daily weather based on site parameters derived from observed weather data. The probability distributions of generated data are statistically similar to the observed data, which implies equality in means and variances, but not in sequence of events. Precipitation occurrence and amount is simulated for each day based on semi-empirical distributions for the succession and transition of dry and wet days. Other weather variables are conditioned on precipitation simulations.
In a second step, the baseline distributions of climatic variables are adjusted by change factors derived from GCM or RCM outputs (i.e. relative differences for precipitation and radiation, and absolute differences for temperature between future and baseline climatic statistics) to generate daily weather series of arbitrary length for the future. No adjustments are made to the distributions of dry and wet series and to temperature variability (Semenov and Barrow 1997; Semenov and Stratonovitch 2010). LARS-WG has been shown to perform well in reproducing various weather statistics (Semenov et al. 1998; Semenov 2008). Bias correction in a post-processing step – correction of the model output towards observations (Ehret et al. 2012) – is not explicitly required because comparison of generated with observed baseline weather data is an inherent part of the WG process.

LARS-WG was selected among various statistical downscaling techniques because of its ability to adjust series of dry-wet spells and generate long data series, and the availability of minimum and maximum temperature data for crop production impact assessment. Long weather series allow to include the natural year-to-year variation of weather and long-term extreme events, and are thus suitable for risk assessment (Porter and Semenov 2005; Semenov 2007).

Notwithstanding the considered choice for LARS-WG in this study, a WG has, like all downscaling techniques, some weaknesses. There is the tendency to underestimate extremes because events outside those present in the observations cannot be reproduced (Wilby and Wigley 1997; Wilby et al. 1998; Fowler et al. 2007; Tebaldi and Knutti 2007; Knutti et al. 2010). Another limitation is the potential underestimation of interannual variance of monthly precipitation sums due to overdispersion and underrepresentation of precipitation persistence. Overdispersion in generated weather data leads to the underrepresentation of series of successive days, for example, with relatively high (or low) temperature, which may cluster in reality (Wilks and Wilby 1999; Kim et al. 2012). LARS-WG performs well for the generation of mean monthly weather variables, but might not entirely capture the variance of observed precipitation data (incl. extremes) (Sunyer et al. 2012; Taye and Willems 2013). In relation to future climate data, a major assumption of the WG technique concerns the relation between the atmosphere and local climatic variables, which is presupposed to remain unaltered in the future. Also, unanticipated (and possibly unrealistic) effects to secondary variables can occur when parameters describing precipitation distributions are modified by climate change factors (Wilks 1992; Wilby and Wigley 1997; 2012).

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Supplementary material 2. GCMs and RCMs from the CMIP3 and ENS ensembles used in this study

Table S-1 Global climate models (GCMs) from CMIP3 and regional climate models (RCMs) from ENS

Model acronym	Research centre	GCM /RCM		Driving GCM for RCM	Grid resolution	Source
GCMs from CMIP3						
BCM2	Bjerknes Centre for Climate Research	GCM	BCM2.0	-	1.9 × 1.9°	(Déqué et al. 1994)
CGMR	Canadian Centre for Climate Modelling and Analysis	GCM	CGCM33.1 (T47)	-	2.8 × 2.8°	(McFarlane et al. 1992)
CNCM3	Centre National de Recherches Meteorologiques	GCM	CNRM-CM3	-	1.9 × 1.9°	(Déqué et al. 1994)
CSMK3	Commonwealth Scientific and Industrial Research Organisation	GCM	CSIRO-MK3.0	-	1.9 × 1.9°	(Gordon et al. 2002; CSMD 2005)
FGOALS	Institute of Atmospheric Physics	GCM	FGOALS-g1.0	-	2.8 × 2.8°	(Wang et al. 2004)
GFCM21	Geophysical Fluid Dynamics Lab	GCM	GFDL-CM2.1	-	2.0 × 2.5°	(Anderson et al. 2004)
GIAOM	Goddard Institute for Space Studies	GCM	GISS-AOM	-	3 × 4°	(Russell et al. 1995)
HadCM3	UK Meteorological Office	GCM	HadCM3	-	2.5 × 3.75°	(Gordon et al. 2000; Pope et al. 2000)
HADGEM	“	GCM	HadGEM1	-	1.3 × 1.9°	(Martin et al. 2006; Ringer et al. 2006)
INCM3	Institute for Numerical Mathematics	GCM	INM-CM3.0	-	4 × 5°	(Galin et al. 2003)
IPCM4	Institute Pierre Simon Laplace	GCM	IPSL-CM4	-	2.5 × 3.75°	(Hourdin et al. 2006)
MIHR	National Institute for Environnemental Studies	GCM	MRI-CGCM2.3.2	-	2.8 × 2.8°	(Hasumi et al. 2004)
MPEH5	Max-Planck Institute for Meteorology	GCM	ECHAM5-OM	-	1.9 × 1.9°	(Roeckner et al. 1996)
NCCCS	National Centre for Atmospheric Research	GCM	CCSM3	-	1.4 × 1.4°	(Collins et al. 2006)
NCPCM	“	GCM	PCM	-	2.8 × 2.8°	(Kiehl et al. 1998; Kiehl and Gent 2004)
RCMs from ENS						
C4IRCA3	Community Climate Change Consortium for	RCM	RCA3.0	HadCM3Q16	25 km	(Kjellström et al. 2005)

	Ireland					
DMI-HIRHAM5	Danish Meteorological Institute	RCM	HIRHAM5	ECHAM5-r3	25 km	(Christensen et al. 2006)
ETHZ-CLM	Swiss Federal Institute of Technology Zurich	RCM	CLM	HadCM3Q0	25 km	(Jaeger et al. 2008)
KNMI-RACMO2	Royal Dutch Meteorological Institute	RCM	RACMO2	ECHAM5-r3	25 km	(van Meijgaard et al. 2008)
METO-HC	UK Meteorological Office	RCM	HADRM3Q3	HadCM3Q3	25 km	(Collins et al. 2011)
MPI-M-REMO	Max-Planck Institute for Meteorology	RCM	REMO	ECHAM5-r3	25 km	(Jacob 2001)
SMHIRCA-BCM	Swedish Meteorological and Hydrological Institute	RCM	RCA3.0	BCM	25 km	(Kjellström et al. 2005)
SMHIRCA-ECHAM	"	RCM	RCA3.0	ECHAM5-r3	25 km	(Kjellström et al. 2005)
SMHIRCA-HadCM	"	RCM	RCA3.0	HadCM3Q3	25 km	(Kjellström et al. 2005)

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Supplementary material 3. Description of the AquaCrop and Sirius crop models

AquaCrop (Raes et al. 2009; Steduto et al. 2009; Vanuytrecht et al. 2014) is a water productivity model that simulates biomass production based on the amount of water transpired from the green canopy cover, which develops based on thermal time and as affected by water stress. Biomass production is linked to crop transpiration, which is also affected by water stress, via the crop water productivity parameter WP*, i.e. a measure for water use efficiency). Besides temperature determining thermal time and pollination success, there is an additional limitation effect on biomass production at cold temperatures. With increasing [CO_2], WP* increases and transpiration decreases. The variable WP* response to CO_2 was set low as recommended for maize with its C4 photosynthetic pathway (Vanuytrecht et al. 2011): WP*increased by 6.5% for a [CO_2] increase to 530 ppm relative to a baseline concentration of 370 ppm. AquaCrop requires daily precipitation, minimum and maximum temperature, and ETo as input data.

Sirius (Jamieson et al. 1998) simulates biomass production from intercepted photosynthetically active radiation and radiation-use efficiency (RUE). Leaf area index (LAI) is developed based on thermal time and phenology follows from leaf appearance, which responds to daylength and vernalization. Water stresses have an effect on LAI and RUE. The latter is proportional to [CO_2] with an increase in RUE of 15.5% for a [CO_2] increase to 530 ppm relative to a baseline concentration of 350 ppm. Sirius required daily precipitation, minimum and maximum temperature, and solar radiation as input data.

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Supplementary material 4. Crop parameters for maize, potato and sugar beet (AquaCrop model) and for winter wheat (Sirius model) for the Flemish Region, Belgium

Table S-2 AquaCrop crop parameters for maize, potato and sugar beet

Parameter [¥]	Value			Units
	Maize	Potato	Sugar beet	
Crop type (2 = fruit/grain producing, 3 = root/tuber)	2	3	3	
Crop is sown (1) or transplanted (0)	1	0	1	
Base temperature below which crop development does not progress	8.0	2.0	5.0	°C
Upper temperature above which crop development no longer increases with an increase in temperature	30.0	26.0	30.0	°C
Total length of crop cycle	1200	1850	1850	GDD
Soil water depletion factor for canopy expansion - upper threshold	0.14	0.20	0.20	
Soil water depletion factor for canopy expansion - lower threshold	0.72	0.60	0.60	
Shape factor for water stress coefficient for canopy expansion	2.9	3.0	3.0	
Soil water depletion fraction for stomatal control - upper threshold	0.69	0.55	0.65	
Shape factor for water stress coefficient for stomatal control	6.0	3.0	3.0	
Soil water depletion factor for canopy senescence - upper threshold	0.69	0.70	0.75	
Shape factor for water stress coefficient for canopy senescence	2.7	3.0	3.0	
ETo-sum threshold during stress period for triggering senescence	0	0	0	mm
Soil water depletion factor for pollination - upper threshold	0.80	0.80	0.80	
Anaerobiotic point at which deficient aeration occurs	5	5	5	vol% below saturation
Minimum air temperature below which pollination starts to fail	10.0	-	8.0	°C
Maximum air temperature above which pollination starts to fail	40.0	-	40.0	°C
Minimum growing degrees required for full biomass production	13.0	8.0	9.0	$°C\cdot day^{-1}$
Crop coefficient when canopy is complete but prior to senescence	1.05	1.10	1.10	
Decline of crop coefficient as a result of ageing, nitrogen deficiency, etc.	0.30	0.15	0.15	$\%\cdot day^{-1}$
Minimum effective rooting depth	0.3	0.3	0.3	m
Maximum effective rooting depth	1.1	0.6	1.0	m
Shape factor describing root zone expansion	13	15	15	
Maximum root water extraction in top quarter of root zone	0.021	0.088	0.025	$m^3\cdot m^{-3}$ $soil\cdot day^{-1}$
Maximum root water extraction in bottom quarter of root zone	0.007	0.022	0.006	$m^3\cdot m^{-3}$ $soil\cdot day^{-1}$
Effect of canopy cover in reducing soil evaporation in late season	50	60	60	
Soil surface covered by an individual seedling at 90% emergence	6.50	20.00	1.00	cm^2
Number of plants per hectare	75000	32000	100000	$plants\cdot ha^{-1}$
Maximum canopy cover	0.87	1.00	0.98	
Crop determinancy linked with flowering	1	0	0	
Excess of potential fruits	50	-	-	%
Water productivity normalized for ETo and CO_2	33.7	18.5	17.0	$g\cdot m^{-2}$
Water productivity ratio normalized for ETo and CO_2 during yield formation	100	100	100	%
Crop performance under elevated atmospheric CO_2 concentration	0	75	50	%

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Reference harvest index	52	90	70	%
Possible increase of HI due to water stress before flowering	0	2	0	%
Positive HI impact of restricted vegetative growth during yield formation	7.0	-	4.0	
Negative HI impact of stomatal closure during yield formation	3	10	-	
Allowable maximum increase of specified HI	15	5	20	%
Period from sowing to emergence	50	150	20	GDD
Period from sowing to maximum rooting depth	1200	650	620	GDD
Period from sowing to start senescence	1100	1550	1450	GDD
Total length of crop cycle from sowing to maturity	1200	1850	1850	GDD
Period from sowing to flowering Length of flowering	650	650	620	GDD
Length of flowering	180	0	0	GDD
Increase in canopy cover	0.013	0.009	0.012	$fraction \cdot GDD^{-1}$
Decrease in canopy cover	0.010	0.008	0.004	$fraction \cdot GDD^{-1}$
Period of harvest index building-up during yield formation	500	1100	1100	GDD

Table S-3 Sirius crop parameters for winter wheat

Parameter	Value	Units
Thermal time from sowing to emergence	150	GDD
Thermal time from anthesis to beginning of grain fill	50	GDD
Thermal time beginning grain fill to end grain fill	650	GDD
Thermal time from end grain fill to harvest maturity	200	GDD
Potential maximum leaf size	0.007	$m^2 \cdot m^{-2}$
Phyllochron	90	GDD
Minimum possible leaf number	8.55	-
Absolute maximum leaf number	24	-
Day length response	0.65	number of leaves per hour of day length
Response of vernalization rate to temperature	0.0012	$°C^{-1}$
Vernalization rate at 0°C	0.015	day^{-1}
PAR extinction coefficient	0.45	-
Maximum protein concentration in unlimited growth conditions [¥]	15	%

[¥] for 15% grain moisture

Supplementary material 5. Schematic presentation of the assessment methodology

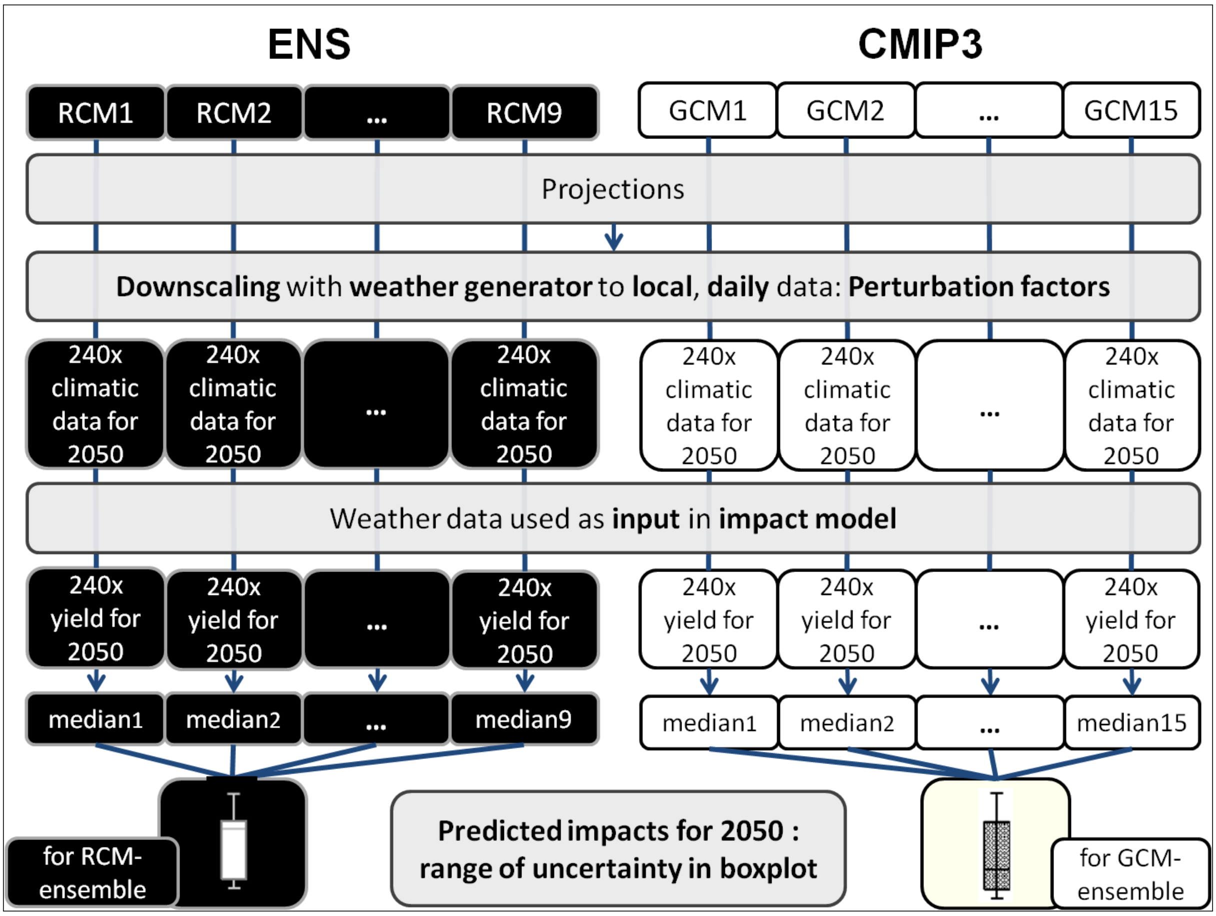

Fig. S-1 Schematic presentation of the assessment methodology for each location from generation of climate data to calculation of the predicted impacts

ENS is the ensemble with fine resolution regional climate models of the EU-ENSEMBLES project; CMIP3 is the ensemble with course resolution global climate models of the Coupled Model Intercomparison Project phase 3.

Supplementary material 6. Projected climatic changes by CMIP3 and ENS multi-model ensembles

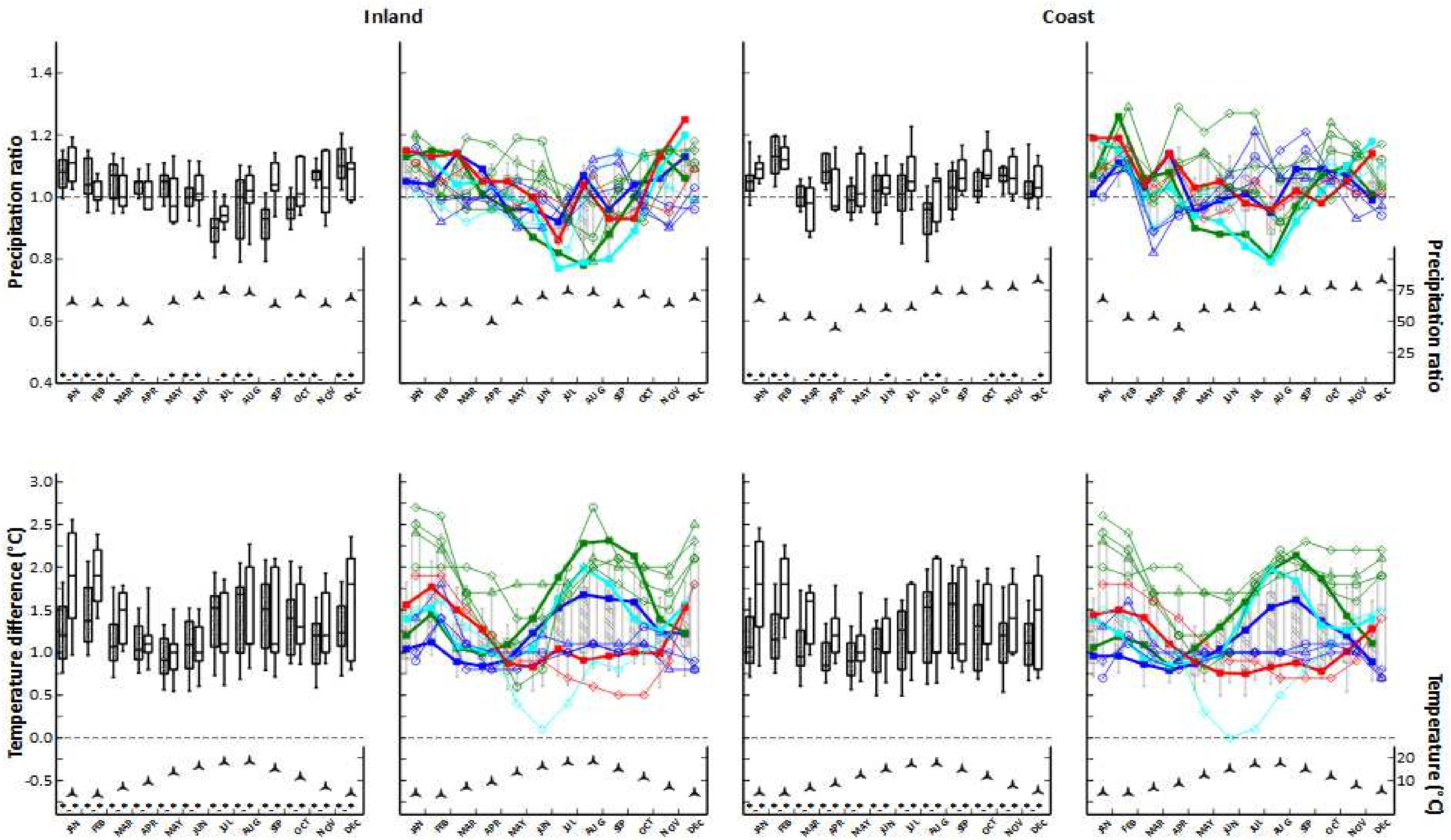

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Fig. S-2 Projected climatic changes by CMIP3 (hatched boxes) and ENS (open boxes) multi-model ensembles.

Relative changes in monthly precipitation (upper row) and absolute changes in monthly mean temperature (lower row) between future climate projections and the baseline for inland (left side) and coastal region (right side).

Boxplots illustrate uncertainty in climate change projections due to model-inherent differences between members of the multi-model ensemble. Box boundaries represent 25- and 75-percentiles, thick line within the box represents the median, whiskers represent 10- and 90-percentiles. Three-armed stars indicate baseline precipitation and temperature on the right Y-axis. The dashed horizontal line reflects no change from the baseline to the future projections. * shows significant change in monthly precipitation or mean temperature (of 240 data) between the ensemble median model and the baseline at threshold probability value $p < 0.05$ according to two-sample Kolmogorov-Smirnov tests.

The coloured lines overlaying background boxplots in figures b-d-f-h indicate projections from individual models. Full symbols represent GCMs, open symbols represent RCMs. Colour key: BCM-family = red; HadCM-family = green; ECHAM-family = dark blue; CNCM-family = light blue.

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Supplementary material 7. Significance of differences in mean yield between the ensemble median and the baseline, or between two ensemble medians for winter wheat, maize, potato and sugar beet

Winter wheat

	Base	InHSCTM	InHSCAM	InHSETM	InHSEAM	InLSCTM	InLSCAM	InLSETM	InLSEAM	CoHSCTM	CoHSCAM	CoHSETM	CoHSEAM	CoLSCTM	CoLSCAM	CoLSETM	CoLSEAM
Base		*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
InHSCTM			*	*		ns				*							
InHSCAM					*		ns				*						
InHSETM					*			ns	*			*					
InHSEAM									ns				*				
InLSCTM							*	*						*			
InLSCAM									*						*		
InLSETM									*							*	
InLSEAM																	*
CoHSCTM											*	ns		ns			
CoHSCAM													*		ns		*
CoHSETM													*			ns	
CoHSEAM																	ns
CoLSCTM															*	ns	
CoLSCAM																	*
CoLSETM																	*
CoLSEAM																	

Maize

	Base	InHSCTM	InHSCAM	InHSETM	InHSEAM	InLSCTM	InLSCAM	InLSETM	InLSEAM	CoHSCTM	CoHSCAM	CoHSETM	CoHSEAM	CoLSCTM	CoLSCAM	CoLSETM	CoLSEAM
Base		*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
InHSCTM			*	*		*				*							
InHSCAM					*		*				*						
InHSETM					*			*	*			*					
InHSEAM									*				*				
InLSCTM							*	*						*			
InLSCAM									*						*		
InLSETM									*							*	
InLSEAM																	*
CoHSCTM											*	*		*			
CoHSCAM													*		*		*
CoHSETM													*			*	
CoHSEAM																	*
CoLSCTM															*	*	
CoLSCAM																	*
CoLSETM																	*
CoLSEAM																	

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Potato

	Base	InHSCTM	InHSCAM	InHSETM	InHSEAM	InLSCTM	InLSCAM	InLSETM	InLSEAM	CoHSCTM	CoHSCAM	CoHSETM	CoHSEAM	CoLSCTM	CoLSCAM	CoLSETM	CoLSEAM
Base		*	*	*	*	*	*	*	*	*	*	*	*	ns	ns	ns	*
InHSCTM			*	*		*				ns							
InHSCAM					*		*				*						
InHSETM					*			*				ns					
InHSEAM									*				ns				
InLSCTM							*	ns						*			
InLSCAM									*						*		
InLSETM									*							ns	
InLSEAM																	ns
CoHSCTM											*	*		*			
CoHSCAM													*		*		*
CoHSETM													*			*	
CoHSEAM																	*
CoLSCTM															*	*	
CoLSCAM																	*
CoLSETM																	*
CoLSEAM																	

Sugar beet

	Base	InHSCTM	InHSCAM	InHSETM	InHSEAM	InLSCTM	InLSCAM	InLSETM	InLSEAM	CoHSCTM	CoHSCAM	CoHSETM	CoHSEAM	CoLSCTM	CoLSCAM	CoLSETM	CoLSEAM
Base		*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
InHSCTM			*	*		*				*							
InHSCAM					*		*				*						
InHSETM					*			ns	*			*					
InHSEAM									*				*				
InLSCTM							*	*						*			
InLSCAM									*						*		
InLSETM									*							*	
InLSEAM																	*
CoHSCTM											*	*		*			
CoHSCAM													*		*		*
CoHSETM													*			*	
CoHSEAM																	ns
CoLSCTM															*	*	
CoLSCAM																	*
CoLSETM																	*
CoLSEAM																	

***** : significant difference between means (of 240 simulations) at threshold probability value $p < 0.05$ according to Mann–Whitney U-tests (or t-tests if data were normally distributed, indicated by black rectangles); **ns** : not significant at threshold probability value $p < 0.05$ according to Mann–Whitney U-tests tests (or t-tests if data were normally distributed)
In: inland; **Co**: coast; **HS**: soil with high totally available water content (TAW); **LS**: soil with low TAW; **C**: CMIP3; **E**: ENS; **TM**: traditional managment; **AM**: adapted management

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