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Using impact response surfaces to analyse the likelihood of impacts on crop yield under probabilistic climate change

Nina Pirttioja[a,*], Taru Palosuo[b], Stefan Fronzek[a], Jouni Räisänen[c], Reimund P. Rötter[d], Timothy R. Carter[a]

[a] Finnish Environment Institute (SYKE), Box 140, 00251 Helsinki, Finland
[b] Natural Resources Institute Finland (Luke), Latokartanonkaari 9, 00790 Helsinki, Finland
[c] Institute for Atmospheric and Earth System Research, P.O. Box 64, 00014 University of Helsinki, Finland
[d] Georg-August-University Göttingen, Grisebachstr. 6, 37077 Göttingen, Germany

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ABSTRACT

Conventional methods of modelling impacts of future climate change on crop yields often rely on a limited selection of projections for representing uncertainties in future climate. However, large ensembles of climate projections offer an opportunity to estimate yield responses probabilistically. This study demonstrates an approach to probabilistic yield estimation using impact response surfaces (IRSs). These are constructed from a set of sensitivity simulations that explore yield responses to a wide range of changes in temperature and precipitation. Options for adaptation and different levels of future atmospheric carbon dioxide concentration [CO_2] defined by representative concentration pathways (RCP4.5 and RCP8.5) were also considered. Model-based IRSs were combined with probabilistic climate projections to estimate impact likelihoods for yields of spring barley (*Hordeum vulgare* L.) in Finland during the 21st century. Probabilistic projections of climate for the same RCPs were overlaid on IRSs for corresponding [CO_2] levels throughout the century and likelihoods of yield shortfall calculated with respect to a threshold mean yield for the baseline (1981–2010).

Results suggest that cultivars combining short pre- and long post-anthesis phases together with earlier sowing dates produce the highest yields and smallest likelihoods of yield shortfall under future scenarios. Higher [CO_2] levels generally compensate for yield losses due to warming under the RCPs. Yet, this does not happen fully under the more moderate warming of RCP4.5 with a weaker rise in [CO_2], where there is a chance of yield shortfall throughout the century. Under the stronger warming but more rapid [CO_2] increase of RCP8.5, the likelihood of yield shortfall drops to zero from mid-century onwards.

Whilst the incremental IRS-based approach simplifies the temporal and cross-variable complexities of projected climate, it was found to offer a close approximation of evolving future likelihoods of yield impacts in comparison to a more conventional scenario-based approach. The IRS approach is scenario-neutral and existing plots can be used in combination with any new scenario that falls within the sensitivity range without the need to perform new runs with the impact model. A single crop model is used for demonstration, but an ensemble IRS approach could additionally capture impact model uncertainties.

1. Introduction

Process-based crop growth models have been used in many studies to estimate future crop yield under changing conditions of atmospheric composition and climate (Asseng et al., 2013; Rosenzweig et al., 2014; Rötter et al., 2018). In the vast majority of previous studies, projections of future anthropogenic climate change are represented as discrete scenarios derived from global climate model (GCM) simulations. Alternative scenarios are commonly selected to represent uncertainties in projected regional climate for variables relevant to crop production, such as temperature and precipitation. Due to the large uncertainties in climate projections, each scenario is typically regarded as equally plausible, while their relative likelihood is not usually considered (Collins et al., 2013). The number of scenarios selected for impact

Abbreviation: IRS, impact response surface

* Corresponding author.
E-mail addresses: nina.pirttioja@ymparisto.fi (N. Pirttioja), taru.palosuo@luke.fi (T. Palosuo), stefan.fronzek@ymparisto.fi (S. Fronzek), jouni.raisanen@helsinki.fi (J. Räisänen), reimund.roetter@uni-goettingen.de (R.P. Rötter), tim.carter@ymparisto.fi (T.R. Carter).

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modelling is commonly limited by the availability of projections for a given region as well as a desire to represent key uncertainties using a manageable (rather than a complete) set of scenarios. The process of selection can hence be somewhat arbitrary and opportunistic. However, with a sufficient number of climate projections used to model yields, the resulting yield distribution can be used to estimate probabilities, for example, of exceeding a given yield threshold. This typically requires applying a large ensemble of climate projections (Challinor et al., 2009; Tao et al., 2018; Tebaldi and Lobell, 2008).

Rather than computing yield distributions by modelling yields for each climate projection separately, another approach makes use of probabilistic climate projections. The idea of representing uncertainties in future climate probabilistically has been discussed extensively by climate scientists (e.g. see summary Collins et al., 2013). Most attempts that apply ensemble GCM outputs compute probabilistic outcomes that are conditional on a given scenario of radiative forcing of the atmosphere by greenhouse gases and aerosols (e.g. Harris et al., 2010; Räisänen and Ruokolainen, 2006). Some projections have been provided to impact analysts as official projections for application (e.g. Murphy et al., 2009 for the United Kingdom). Such projections are of interest for crop modelling because, coupled with impact response surfaces (IRSs – see below), they offer an alternative approach for computing likelihoods of yield estimates under scenarios of future radiative forcing.

In this study, we utilise probabilistic projections of climate change derived from an ensemble of GCM simulations included in the Coupled Model Intercomparison Project Phase 5 (CMIP5 – Taylor et al., 2012) to demonstrate how climate uncertainties evolve throughout the 21st century. Impact likelihoods are addressed by superimposing the probabilistic climate change projections on IRSs, constructed from the results of a sensitivity analysis of barley yield using a crop simulation model. This “IRS-based” approach is used here to analyse impacts under current management and in response to potential adaptation options based on different assumptions about cultivar characteristics and crop management. Through the selection of yield thresholds that are of relevance for stakeholders, the approach can be used to communicate likelihoods of such thresholds being exceeded (Dessai and Hulme, 2004; Jones, 2000).

This work builds on earlier studies using IRSs to examine modelled sensitivities of wheat yield to climate change across a large ensemble of crop models (Fronzek et al., 2018a; Pirttioja et al., 2015; Ruiz-Ramos et al., 2018). These studies found IRS plots to be useful for evaluating model sensitivities and identifying impact discontinuities as well as potential model, data and transcription errors. Here we employ a single crop model for barley, refining the methods of the sensitivity study by introducing seasonality to the perturbations of the baseline climate and accounting for the effects of increasing levels of atmospheric CO_2 concentration [CO_2]. Through these refinements, IRSs applicable to individual [CO_2] levels can then be related to future projections of climate change for estimating crop yield impact likelihoods. While it is acknowledged that using an ensemble of crop models may result in more robust yield estimates (e.g. Asseng et al., 2013), a single crop model was chosen for exploring and illustrating the method. Extending the analysis to cover aspects related to inter-model uncertainty using ensemble crop modelling would be a next step (e.g. Rötter et al., 2012a), but resources for such simulations were not available for this study.

Although applied here in the context of agriculture, the IRS-based approach for estimating impact likelihoods can be applied to a wide variety of impacts. While there have been some earlier applications of the approach for wheat yields (Børgesen and Olesen, 2011; Ferrise et al., 2011; Luo et al., 2007), it also has been applied to permafrost features (Fronzek et al., 2010) and hydrology (Holmberg et al., 2014; Wetterhall et al., 2011). In comparison to earlier applications for wheat, the present study for barley applies new probabilistic projections of future climate and also considers the effect of adaptation measures on likelihoods. Due to the nature of the IRS-based method, this approach for estimating impact likelihoods offers various advantages not as easily achieved with more common scenario-based approaches, including an ability to view probabilistic climate projections in relation to impact behaviour and thresholds on the same diagram as well as a rapid, consistent and comparable method for assessing likelihoods across sectors, regions and scenarios.

The overall objective of the study is to explore the applicability of the IRS-based approach for estimating likelihoods of achieving certain yield outcomes using one model and location as an example. Specifically, the paper aims to: (1) examine the sensitivity of barley yield to a plausible range of perturbations in climate and [CO_2] under Finnish conditions using a process-based crop model, (2) introduce a newly derived set of probabilistic projections of future climate during the 21st century based on the CMIP5 ensemble of global climate models, (3) present an approach for combining IRSs with probabilistic climate projections for analysing the likelihood of specified modelled impacts of climate change on barley yield, (4) illustrate its application to test the potential effect of adaptation options related to crop phenological development and time of sowing on yield response and (5) assess the applicability of the IRS-based approach through comparison against a more conventional scenario-based approach for estimating likelihoods.

2. Material and methods

2.1. General approach

The crop growth simulation model WOFOST was applied in the study to analyse crop responses of spring barley (*Hordeum vulgare* L.) on clay loam soil at Jokioinen (60°48′N, 23°30′E; 104 m a.s.l) in south-western Finland. Barley is widely cultivated in the region covering over a quarter of the total cultivated area in 2017 (OSF, 2017). The widely grown two-row spring barley cultivar Scarlett (Finnish Food Safety Authority Evira, 2017) was used as the default for model simulations. Daily weather observed during the 1981–2010 period was used as the baseline climate and perturbed following procedures outlined below, using different methods to represent anticipated changes in climate during the 21st century. Different options, of relevance for demonstrating the use of the IRS-based approach, were tested for initialising soil characteristics, describing future climate and [CO_2] and representing possible adaptation responses (Table 1).

2.2. Crop model

WOFOST (WOrld FOod STudies) model, version 7.1 (e.g. Boogaard et al., 2014; van Ittersum et al., 2003) simulates crop production potentials dynamically on the basis of crop genetic characteristics, management practices and environmental conditions (soils and climate). The major processes incorporated in WOFOST are temperature-dependent phenological development, CO_2 assimilation, transpiration,

Table 1
Summary of the different aspects assessed in the study (rows) with default and other options tested (columns) and the subsections in which these are described.

Aspect	Default	Other options tested	Subsection
Radiative forcing scenario	RCP8.5	RCP4.5	2.3.3
Soil characteristics	Clay loam	Coarse sand	2.4.1
Sowing date	Adapted	Baseline	2.4.2
CO_2 concentration	Time dependent	Baseline	2.4.3
Seasonality of climate change	Seasonal weighting	Constant annual	2.4.4/2.4.5
Barley cultivars	Scarlett	Annabell; Cultivars 1–10	2.4.6

respiration, partitioning of assimilates to the various organs and yield formation. The model can be used to calculate potential production and two types of limitation to production (water- and nutrient-limited). The soil water balance is based on a relatively simple "tipping bucket" approach. Yield effects of evaporative loss due to water shortage and of oxygen deficit in a wet soil can be accounted for. Yield losses due to pests, diseases, weeds and various extreme weather events such as heat and cold stress and damage from flooding are not considered. Parameter sets for Scarlett and the two soil types (clay loam and coarse sand) under Finnish conditions were adopted from a previous calibration of WOFOST reported in Rötter et al. (2011). WOFOST has been further tested in Rötter et al. (2012b), where it was among the best performing of nine models regarding yield estimations for seven sites in northern and central Europe (including Jokioinen). Applications of the model for barley in Finland are also presented in Rötter et al. (2013) and Palosuo et al. (2015).

Model simulations were performed on a daily time-step for water-limited yields assuming optimal nutrients. Simulations were conducted as a succession of independent growing seasons with the same initial conditions at the beginning of each season.

2.3. Data

2.3.1. Sowing dates and yields

Data regarding observed sowing dates as reported by farmers were obtained from the Evira database collected for quality monitoring of the Finnish grain harvest (Finnish Food Safety Authority Evira, 2012). The dataset includes sowing dates from 1988 to 2012 for barley aggregated to 20 sub-national regions across Finland (on average 38 observations per year and region). The data were used to develop a temperature-based calculation method for defining the sowing dates used in the model simulations (see subsection 2.4.2).

Observed dry matter (DM) grain yields from Finnish official variety trials at Jokioinen during the baseline period (1981–2010 – Kangas et al., 2010) were used for comparison against simulated yields from WOFOST. The data comprised aggregated annual yields for cultivars classified according to their phenological properties based on the length of the growth cycle (Palosuo et al. (2015). The data used for this study were for the cultivar group classified as having an intermediate development rate, which includes Scarlett. Observations are from all soil types to increase the sample size. The observed yields are adjusted to account for long-term trends assumed to be unrelated to weather by removing a linear trend.

2.3.2. Baseline weather data

Observed daily weather data at Jokioinen during the baseline period (1981–2010) were obtained for the following variables: global radiation, minimum and maximum temperature, precipitation, wind speed and minimum and maximum relative humidity. Daily mean wind speed was calculated as the average of 3-hourly measurements at 10 m height, converted to a height of 2 m assuming the logarithmic wind profile of Allen et al. (1998; their eq. 47). Daily mean vapour pressure was calculated as a function of relative humidity and temperature (Allen et al., 1998; their eqs. 11 and 17).

2.3.3. Future climate change data

Future climate change was represented as regional temperature and precipitation changes for radiative forcing described by the intermediate (RCP4.5) and high (RCP8.5) representative concentration pathways (RCPs – van Vuuren et al., 2011). Changes are based on projections from the CMIP5 ensemble of GCM simulations (Taylor et al., 2012). A resampling method for deriving probabilistic projections, developed by Räisänen and Ruokolainen (2006), was applied to derive the RCP-projections used here. The method accounts for natural climate variability by identifying other time intervals in the model simulations having the same ensemble global mean temperature change as was projected for the interval between the reference period (1981–2010) and a given target period, and then extracting the individual GCM changes projected for Finland over those other time intervals (resampling – as described in Supplement 1). Surfaces of the joint probability of temperature and precipitation change for a 2.5 × 2.5-minute grid cell over Jokioinen were constructed relative to 1981–2010 for seven future 30-year time periods (2011–2040, 2021–2050, …, 2071–2099) centred on years from 2025 to 2085 in 10-year intervals (hereinafter referred to as 2025, 2035, …,2085, respectively). The resampled projections were also used to construct conventional climate scenarios (see section 2.4.5).

2.4. Model application

2.4.1. Soil characteristics

The default soil for the model simulations was clay loam. As a test of model sensitivity to soil characteristics and to cover the wide range of agricultural soils found in Finland, simulations were also performed assuming a soil type with a much lower water holding capacity, coarse sand. For more details of selected soil parameters, see Supplement 2 and Rötter et al. (2011).

2.4.2. Sowing and harvest dates

The sowing date of the crop was calculated following the method proposed by Carter and Saarikko (1996) for wheat, where the sowing date is specified as the day when the smoothed daily mean temperature exceeds a defined threshold in the spring. The applicability of the method for barley was tested against observed sowing dates (1988–2012) at locations across Finland obtained from the Evira database (Finnish Food Safety Authority Evira, 2012). There was large scatter in the observed sowing dates and the best performing model (root mean square error = 12.3 d, mean error = 1 d) was for a 7-day moving average of daily mean temperature observations exceeding a threshold temperature of 11 °C. The sowing date was specified as the day when the middle day of the averaging period crosses the threshold temperature. Using the middle day of the averaging period assumes that in the decision to sow, a farmer could take into account the weather of the past three days and the forecast for the following three days. Day of year (DOY) 60 is defined as an earliest start for the calculations. This is an approximation of the date when the long term mean minimum temperatures are estimated to rise above zero under the highest warming (8 °C) projected for the study area by the end of the century. On dates earlier than this, even under the warmest projected climate, the high likelihood of freezing conditions would not be conducive to soil preparation or seed germination.

Simulations were allowed to continue to the end of the year, but in post-processing of the simulation results a dynamically-defined harvest cut-off date was imposed. If a simulation reported a harvest date later than the day when the 7-day moving average of daily minimum temperature fell below 3 °C in the autumn (checked only after DOY 212), DM grain yield was set to 0 kg ha^{-1}. On average this coincides with the first occurrence of minimum temperature falling below 0 °C. It is assumed that if the crop was not yet simulated to be fit for harvest, the freezing temperatures would damage the crop and no yield would be recorded. During the baseline period the average harvest cut-off is at the end of September on DOY 267.

2.4.3. Crop parameter adjustments for different CO_2 concentrations

An increase in [CO_2] is known to stimulate photosynthesis and enhance water use efficiency, leading to increased plant productivity, particularly in C_3 crops such as barley (e.g. Kimball et al., 2002; Tubiello et al., 2007). These effects were incorporated by modifying values of three crop growth parameters that reflect CO_2-related changes in plant behaviour following the approach reported in Reidsma et al. (2015). The equations used to modify the parameters are given in Supplement 3. Model simulations were performed for 15 different

[CO_2] levels, representing years from 2025 to 2085 in 10 year intervals for RCP4.5 and RCP8.5 and the baseline (1995) level (Table S2, Supplement 3).

2.4.4. Sensitivity analysis and construction of impact response surfaces

The sensitivity of barley yields to changes in key climate variables was tested by systematically modifying temperature and precipitation values of baseline weather data using a simple "change factor" approach (e.g. Diaz-Nieto and Wilby, 2005). Observed annual mean temperatures were modified by between -3 °C and +8 °C at 1 °C intervals with one additional increment at 0.5 °C (13 increments; hereinafter referred to as Δt) and annual precipitation by between -15% and +40% at 5% intervals (12 increments; δp), totalling 156 (13 × 12) different combinations of changes to temperature and precipitation. Ranges of the increments were selected to encompass changes in regional climate change at Jokioinen throughout the 21st century represented in the climate projections used in the study and described in subsection 2.3.3 (see also the light grey annual box plots on the left hand side of Figures S1a and b, Supplement 4). The intervals of the changes were chosen to be fine enough to capture possible non-linearities in model responses to a changing climate, while at the same time ensuring a manageable number of combinations.

Seasonal weighting was applied to the annual changes to reflect the seasonal pattern of future change projected by climate models (Supplement 4). As a result, a given annual change varies throughout the year, e.g +2 °C translates into seasonal changes varying between +1.7 °C (in summer) and +2.5 °C (in winter). The seasonal changes were interpolated linearly to daily values, which were then applied as perturbations to daily temperature and precipitation for each year of the baseline time period. To assess the effect of applying a seasonal pattern in adjusting the daily values of temperature and precipitation, an additional set of model simulations was performed for the cultivar Scarlett by applying Δt and δp as constant changes throughout the year to the baseline values. Note that potential changes in inter-annual and daily variability are not accounted for when perturbing baseline weather, which might alter the intensity and distribution of precipitation or the frequency of extreme heat or cold events.

It was assumed that daily relative humidity would remain unchanged from the baseline as temperature changed (e.g. Lorenz and DeWeaver, 2007), requiring adjustment of daily vapour pressure as a function of temperature following the method of Allen et al. (1998; their eqs. 11 and 17). All other variables were kept unchanged at their baseline values.

Crop model results for the combinations of perturbations described above were plotted as interpolated contour lines with respect to changes in annual temperature along the x-axis and precipitation along the y-axis to construct IRSs (Pirttioja et al., 2015). Individual IRSs were created in this way, each for a unique combination of parameters (harvest year, soil type, future [CO_2] and adaptation options).

2.4.5. Conventional climate scenario-based approach

Crop yields were also simulated using a conventional scenario construction method with individual GCMs for comparison with the IRS-based approach. For this purpose, a second set of adjusted weather data files was prepared by applying directly the seasonal changes projected by individual GCMs under RCP8.5 for each of the seven future time periods (including, in addition, resampled changes) to the observed baseline temperature and precipitation. Due to the resampling method used the sample sizes of individual projections of seasonal change (from individual GCMs plus resampled changes) vary between 126 and 462 for RCP8.5 depending on the time period (see Supplement 1). These seasonal changes were first linearly interpolated to daily values and equations S5-7 of Supplement 4 were used to adjust the observed values of temperature and precipitation and to correct the daily precipitation changes to match the projected annual precipitation of each GCM simulation for each time period. [CO_2] levels were the same as for the RCP8.5 simulations in the IRS-approach (Table S2, Supplement 3).

Table 2
Temperature sum combinations defined for each cultivar from emergence to anthesis (TSUM1) and anthesis to maturity (TSUM2).

TSUM1	TSUM2 (°C d)			
(°C d)	600	610	710	830
700	Scarlett	–	Cultivar 3	Cultivar 7
750	–	Annabell	Cultivar 4	Cultivar 8
770	Cultivar 1	–	Cultivar 5	Cultivar 9
800	Cultivar 2	–	Cultivar 6	Cultivar 10

2.4.6. Adaptation options

As a potential adaptation option, alternative barley cultivars to Scarlett were identified that represent different rates of phenological development, defined simply on the basis of their thermal requirements (°C d) from emergence to anthesis (TSUM1) and from anthesis to maturity (TSUM2). Values for Scarlett and Annabell represent existing cultivars, whereas values for Cultivars 1 to 10 were chosen to represent a wide range of TSUM values (Table 2). The ranges were set to cover those used in Rötter et al. (2011) to design cultivars identified as providing potential for better exploiting extended growing seasons under warming.

As a complementary adaptation measure, the effect of sowing date on the model results was tested by defining it in two ways. The first represents autonomous adaptation through “optimal” sowing with respect to temperature, applying the sowing date model described in subsection 2.4.2 to baseline and perturbed temperatures (hereinafter referred to as adapted sowing). The second method represents a situation without adaptation, where sowing dates calculated using the same sowing date model for the baseline years are kept fixed for all perturbations (referred to as baseline sowing).

2.5. Estimating the likelihood of impacts

For estimating the likelihood of a specified impact occurring in the future, it is necessary to evaluate the probability that future climate change could induce such an impact. This is illustrated in Fig. 1. Joint frequency distributions of future 30-year mean temperature and precipitation change were fitted to the resampled projections for each time period (subsection 2.3.3) using a kernel density estimation technique (grey shading in Fig. 1). On the resultant plotted surface, combinations of projected temperature and precipitation change clustered with a high frequency in the centre of the distribution are interpreted as having a higher probability than outliers at the margins of the distributions. The climate surfaces were next superimposed onto the IRSs of mean yields created from the results of the sensitivity analysis (coloured surface in Fig. 1).

In this study a critical impact was defined as a shortfall of future 30-year mean yield relative to a threshold mean yield (6000 kg ha^{-1}). By identifying the threshold yield with respect to temperature and precipitation change on the IRS and integrating over the parts of the joint frequency distribution of future climate falling below the defined threshold, the likelihood of yield shortfall can then be calculated. In practice, the procedure involved computing the percentage of resampled projections (red points in Fig. 1) lying in regions of the IRS with estimates below the yield threshold. By superimposing the probabilistic projection for a specific time period onto an IRS representing the same time period and accounting for [CO_2] levels corresponding to the RCP projection of interest (Supplement 3, Table S2), the evolution of the likelihood of yield shortfall throughout the century can be presented.

Uncertainty information relating to the future climate change (CC) and to aspects of inter-annual variability (IAV) can also be presented

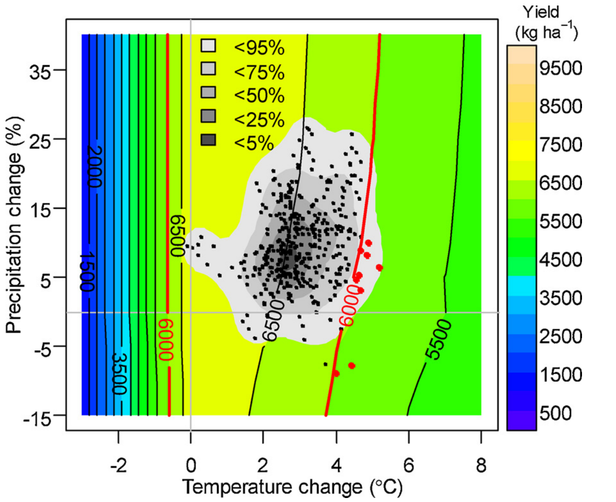

Fig. 1. An example of an impact response surface (IRS) for 30-year mean grain yield (kg ha^{-1}) with a threshold of 6000 kg ha^{-1} shown as a red contour line. Resampled GCM projections of a future period-mean temperature and precipitation change are superimposed on the IRS (points and grey shading). Red points indicate those projections that fall below the yield threshold and black points those above. Relative frequencies of changes relative to 1981–2010 are also shown as grey shading (for details, see text). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

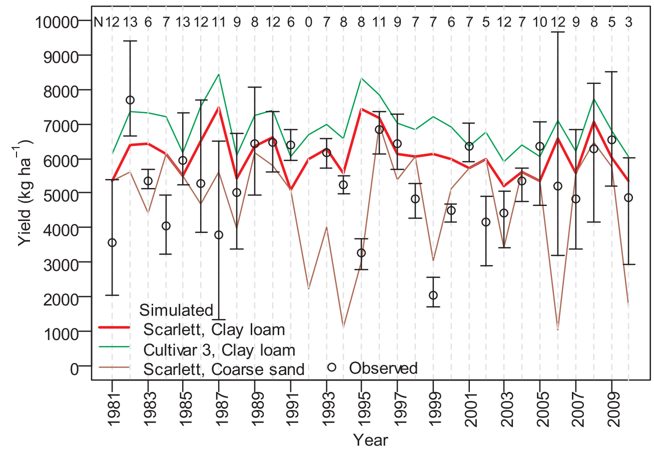

Fig. 2. Dry matter grain yields (kg ha^{-1}) of spring barley for the 1981–2010 baseline period at Jokioinen, Finland. Simulations: Scarlett on clay loam (bold red line); Scarlett on coarse sand (brown line); Cultivar 3 on clay loam (green line). Observations: de-trended annual mean yields from official variety trials (Kangas et al., 2010) for cultivars classified as intermediate (Palosuo et al., 2015) based on their development rate including all soil types (circles). Whiskers denote annual yield minima and maxima. The number of observations per year (N) is indicated at the top of the figure. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

using this approach with respect to average yield for different cultivars during the coming century. The evolution of average yield levels throughout the century was estimated by first interpolating 30-year mean yields on the IRS to each resampled climate change projection and then taking the median of those. Low-end estimates of future yield were investigated for each period by using the 10th percentile IRSs of annual yields (i.e. the 1-in-10 year lowest yields for a given [CO_2] level – the IAV component of uncertainty), interpolating these values to each resampled climate change projection and then identifying the 10th percentile yield across the projections, indicating the 10% least favourable climate (the CC component of uncertainty). Conversely, estimation from 90th percentile IRSs with climates giving the 90th percentile yield allows an examination of the highest yields (IAV) under the 10% most favourable future climates (CC).

The IRS-based approach to computing likelihoods of barley yield shortfall was compared to a more conventional scenario-based approach (see subsection 2.4.5). For the conventional scenario-based approach we calculated the likelihood of yield shortfall (< 6000 kg ha^{-1}) across all ensemble members in a given time period after first averaging across the 30 individual years in each ensemble member. The likelihood was calculated as the number of 30-year mean yields below the threshold relative to the full ensemble, offering direct comparison against the results from the IRS-based approach.

3. Results

When describing the results default settings are assumed (Table 1) unless otherwise indicated.

3.1. Model performance under baseline conditions

During the baseline period (1981–2010) simulated 30-year mean DM grain yield for the default settings (cultivar: Scarlett, soil: clay loam) was 6082 kg ha^{-1}. Annual yields ranged from 5104 to 7458 kg ha^{-1} (Fig. 2). When assuming coarse sand, with a much lower water holding capacity, annual yields were more sensitive to water shortage. This led to larger yield fluctuations with annual yields ranging from 1025 to 6989 kg ha^{-1} (mean 4734 kg ha^{-1}).

Simulated yields (for Scarlett on clay loam) exceed the observed yields during most years. Some large deviations are found during years with exceptionally challenging weather conditions for crop cultivation such as 1987 and 1995. During these years observed yields were low due to issues such as late thawing of the soil in the spring delaying sowing and excessive moisture causing lodging and hindering sowing and threshing (Kettunen, 1988, 1996). However, such issues are not included in the model and thus the challenges are not reflected in the simulated yields. In some years simulated yields fall short of observations, for example in 1991 when a cool early summer results in a very late calculated sowing date 27 days later than the near-average date actually observed. Overall, the RMSE of simulated versus observed yields was 1604 kg ha^{-1}, a value consistent with estimates in an earlier inter-comparison study of nine barley simulation models for northern and central Europe, including Jokioinen (Rötter et al., 2012b). Simulated yields of Cultivar 3 are also shown in Fig. 2, to illustrate the performance of a cultivar with a higher temperature requirement for TSUM2 than Scarlett (Table 3). The pattern of inter-annual yield variability of Cultivar 3 remains mostly unchanged when compared to that of Scarlett but the yields are on average 807 kg ha^{-1} higher per year.

3.2. Sensitivity of barley yield to climate change

Results of the sensitivity analysis of barley yield responses to changes in temperature and precipitation are presented as percentage changes in 30-year mean yields relative to the baseline for Scarlett on clay loam (Fig. 3a) and coarse sand (Fig. 3c) for baseline [CO_2] of 360 ppm. On both soils the maximum yields are found close to baseline temperatures (green areas) with yields decreasing with temperature changes in both directions. With warming the decrease is gradual over a large gradient of temperature changes with the maximum decline being -27% on clay loam and -49% on coarse sand at +8 °C (Δt) and -15% (δp). In contrast, the decline in yields relative to the baseline occurs very rapidly across all δp for cooling, by up to -85% on clay loam and -84% on coarse sand at -3 °C (Δt) and -15% (δp). Simulations for clay loam are fairly insensitive to precipitation change, depicted by the nearly vertical contour lines in Fig. 3a. Results for coarse sand show greater sensitivity to precipitation, particularly with high temperature

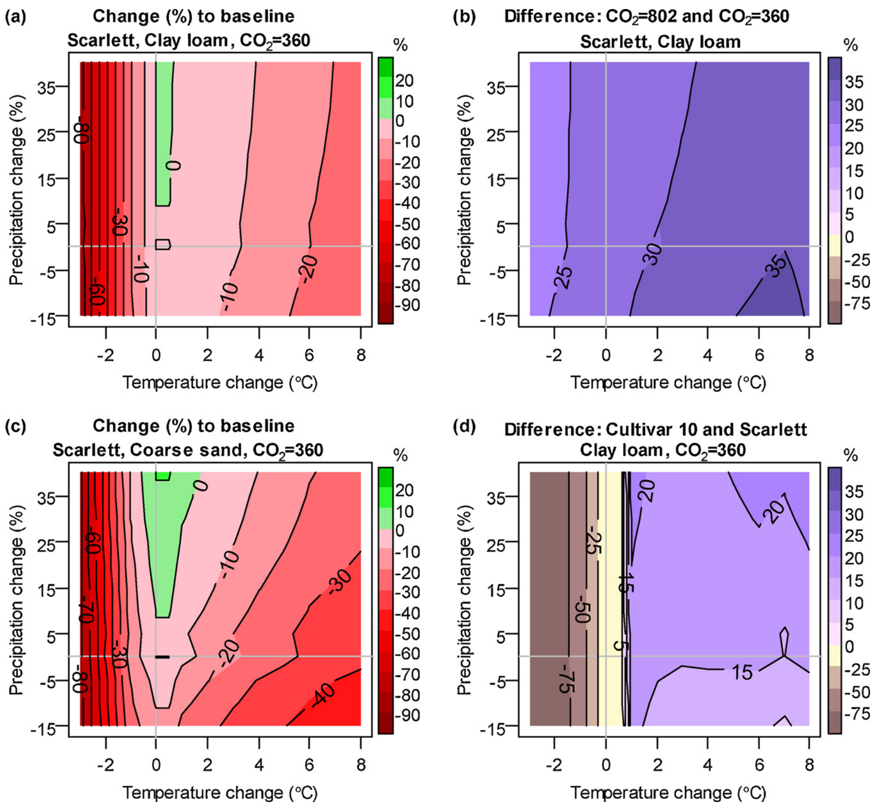

Fig. 3. Left column: modelled response (%) to changes in temperature (x-axis) and precipitation (y-axis) of 30-year mean dry matter grain yields relative to the baseline (1981 – 2010) climate (intersection of grey lines) for Scarlett at 360 ppm on (a) clay loam and (c) coarse sand. Right column: differences (%) in yield response relative to default IRS values for Scarlett (360 ppm) assuming (b) elevated [CO_2] in 2071 – 2099 (802 ppm) and (d) use of Cultivar 10. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

increase (Fig. 3c).

With a higher [CO_2], yields are enhanced under all combinations of perturbed climate, with increasing temperature accentuating this effect. The greatest benefit is found with the most severe temperature changes in combination with decreases in precipitation (Fig. 3b).

The benefits associated with a longer developing cultivar are found with warming above 0.5 °C, where period-mean yields for Cultivar 10 are consistently higher than for Scarlett and further benefit from increased precipitation. On the other hand, Scarlett out-yields Cultivar 10 under baseline temperatures and progressively more so with lower temperature (Fig. 3d).

3.3. Likelihood of yield shortfall throughout the 21st century

In order to compute likelihoods of 30-year mean yield shortfall in the future, we adopted a yield threshold of 6000 kg ha^{-1}, which is the approximate 30-year baseline mean yield simulated by WOFOST for Scarlett (cf. Fig. 2). This is used as a hypothetical example of a present-day yield level that farmers might not wish to see decline in the future.

When elevated [CO_2] is accounted for in model simulations the estimated likelihood of future yield shortfall is reduced substantially compared to that under a fixed baseline [CO_2] level (contrast solid and dashed red lines; bottom graph of Fig. 4). This is because the climate change projections (grey shaded areas) shift to warmer conditions in the future where yields progressively decline below the threshold (upper and lower panels). However, with elevated [CO_2] included (cf. Fig. 3b), its effects more than compensate for yield reductions due to higher temperatures (the IRS isolines shift more than the climate projections), and modelled yields exceed 6000 kg ha^{-1} under most or all projected future climates (solid red line; bottom graph).

The effect of using the seasonal change method as opposed to applying constant changes can be seen by comparing the solid red line with the short dashed line (bottom graph). For the seasonal change method, including elevated [CO_2] (solid red line), the likelihood of yield shortfall is at its highest level (13%) during the first future time period (2011–2040) after which it declines to 0% from 2041 to 2070 onwards. Using constant changes (red dotted line) the likelihood of yield shortfall remains higher throughout the century, fluctuating between 5% and 24% from one period to another. Likelihoods are also plotted for the scenario-based approach (30-year mean, time-dependent [CO_2]), which shows that the IRS-based approach slightly underestimates the likelihood of yield shortfall (on average by 4% – solid red line versus black line in Fig. 4, bottom graph).

With respect to the effectiveness of cultivar choice and time of sowing as options for adaptation, Cultivars 3–10 show little to no likelihood of falling short of the threshold even with no change from baseline sowing (Fig. 5), when applying the IRS-based approach. The remaining group of four cultivars (Scarlett, Annabell and Cultivars 1–2) differ from the others in their response. These show elevated likelihoods of yield shortfall in the time periods closer to the baseline, which start to decrease when moving further into the future. Cultivar 2 has the highest likelihood of yield shortfall. In contrast to the declining likelihood of shortfall under RCP8.5, the trend in likelihood under RCP4.5 reverses after mid-century, reaching higher levels than for RCP8.5 for the four cultivars from 2045 onwards (Fig. 5, bottom panel). The benefit of adapting the sowing date to suit the temperature of the given conditions is well demonstrated for the same cultivars under RCP8.5, with likelihoods of yield shortfall under baseline sowing being considerably higher than those for adapted sowing (Fig. 5 middle and top, respectively).

3.4. Evolving yield levels and associated uncertainties

Modelled yield responses of different barley cultivars under RCP8.5 are analysed in more detail in Fig. 6. Under the median projected climate, the 30-year mean yield responses of cultivars fall into three distinct groups (Fig. 6a). Scarlett, Annabell and Cultivars 1–2 have the lowest mean yields throughout the future time periods. Results for Scarlett using the scenario-based approach are also shown (black dots) and are nearly identical to those of the IRS-based approach until the

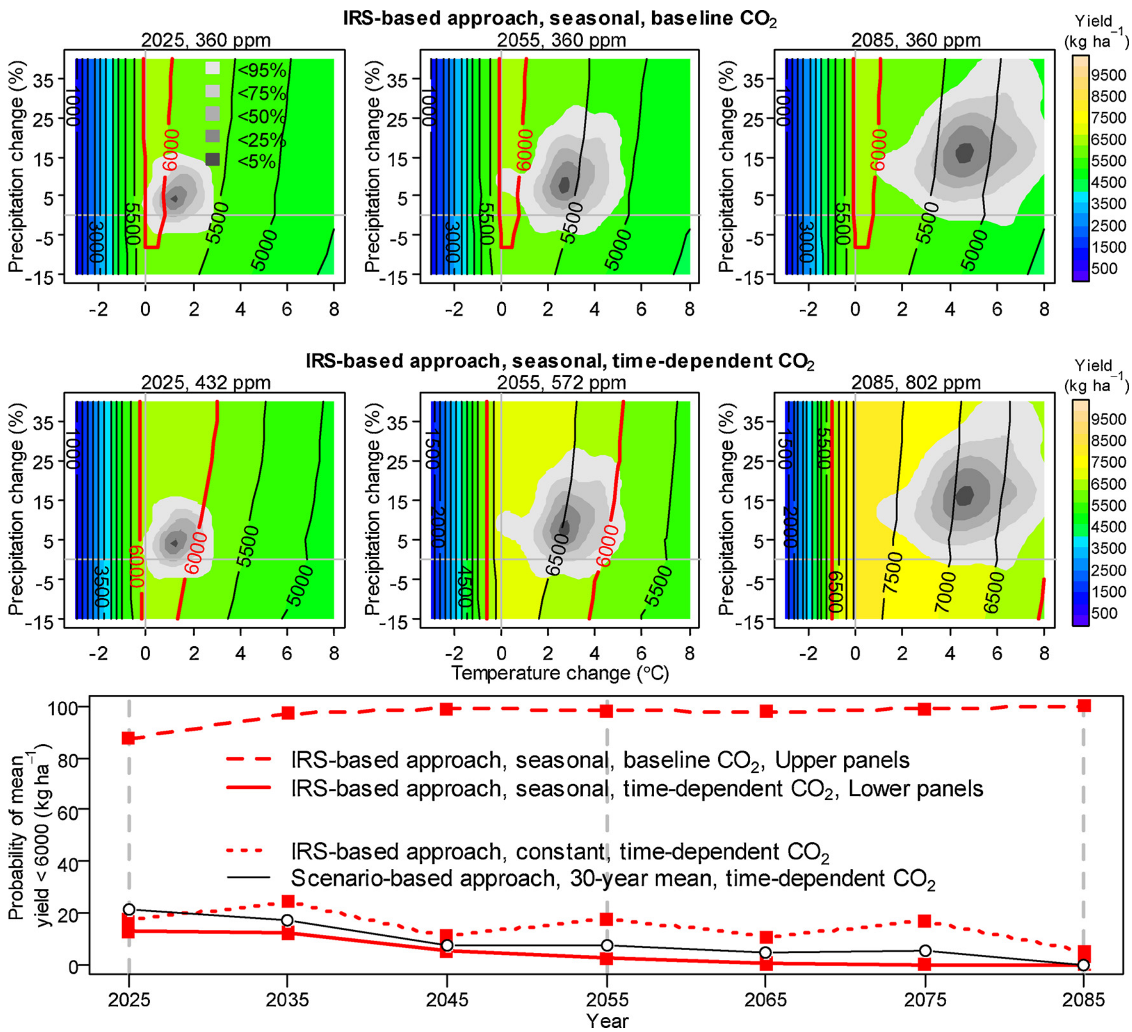

Fig. 4. Likelihood of future 30-year mean yield shortfall under RCP8.5. Top six panels: IRSs of grain yield (kg ha^{-1}) for Scarlett applying the seasonal change method for 30-year time periods centred on 2025, 2055 and 2085 with resampled relative frequencies of projected temperature and precipitation change relative to 1981–2010 superimposed (shaded areas) for baseline [CO_2] (upper panels) and RCP8.5 [CO_2] (lower panels). The 6000 kg ha^{-1} yield threshold is delineated in red. Bottom graph: Likelihood of 30-year mean yield falling short of the threshold estimated at 10-year intervals out to 2085 under RCP8.5. Periods with IRS plots shown above are indicated with vertical grey lines. Simulations: baseline [CO_2] and changed climate using the seasonal method (dashed red line); future [CO_2] and changed climate using the seasonal (solid red line) and constant change (dotted red line) methods. Also shown are likelihoods based on a conventional scenario-based approach for resampled ensemble GCM projections across 30-year mean yields (solid black line). For explanation, see text. For default settings other than those specified here, see Table 1. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

end of the century. In contrast, Cultivars 9–10 produce lower mean yields for the baseline period, but considerably higher yields in the future. Responses are similar for Cultivars 7 and 8 (the two highest yielding cultivars in the future), but these also show somewhat higher baseline yields than existing varieties. Cultivars in the third group (3–6) are among the highest yielding during the baseline but are out-yielded in the future by Cultivars 7-10.

More detailed scrutiny of Scarlett and Cultivar 10 reveals that under baseline conditions the mean yield for Cultivar 10 is reduced by cases of zero yield, although the highest yields are considerably higher than for Scarlett (Fig. 6b). Though lower yielding during many years, simulated yields for Scarlett are more reliable with no failures under baseline conditions (minimum yields not shown). After 2035, Cultivar 10 outperforms Scarlett in every respect: both the highest yields (in the 90th percentile years under the most favourable 90th percentile climates) and lowest yields (10th percentiles of both) exceed those for Scarlett. Period-mean yields are also higher. Apart from the first future time-period (2025) for Cultivar 10, most of the uncertainty around the mean yield is due to inter-annual variability. Note that the baseline uncertainty range encompasses only the inter-annual variability for the observed climate.

4. Discussion

4.1. Yield sensitivities

Results of the sensitivity analysis for the present-day cultivar, Scarlett, suggest that it is well adapted to the current climate (see Figs. 3a and c). A similar result was found for wheat in (Pirttioja et al., 2015). Highest yields are obtained close to baseline temperature, but with any change in temperature yields decline. Under warming, plant phenological development is accelerated, providing less time for allocation of dry matter to the grain, thus resulting in lower yields (e.g. Kontturi, 1979; Peltonen-Sainio et al., 2011; Rötter et al., 2011). However, the inclusion of elevated [CO_2], through its beneficial effects on crop growth and water use efficiency (see also Fig. 3b), compensates for yield losses with temperature increase and drying (and see 4.2.3, below). For cooling, the crop may fail to reach maturity in time for harvest (estimated using a temperature-based method). This procedure and the assumption made to set the yield to zero during such years are

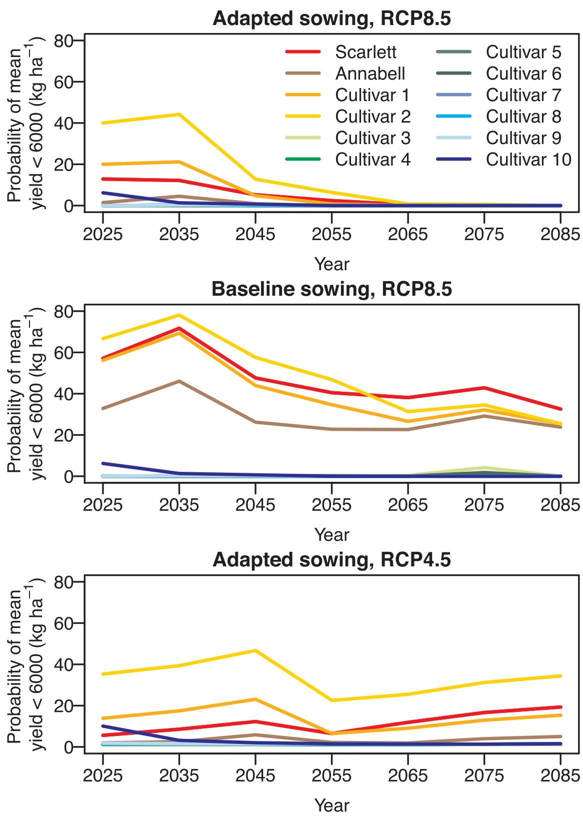

Fig. 5. Estimated likelihood of barley yield shortfall (30-year mean yield < 6000 kg ha^{-1}) for 30-year time periods centred on years from 2025 to 2085 in 10-year intervals under RCP defined probabilistic climate and [CO_2] for Scarlett, Annabell and 10 adapted cultivars using the IRS-based approach. Top: adapted sowing for RCP8.5; Middle: baseline sowing for RCP8.5; Bottom: adapted sowing for RCP4.5. For default settings other than those specified here, see Table 1. Note that several lines with likelihoods close to zero are overlapping and obscure each other even though the values may differ marginally. (For interpretation of the colours, the reader is referred to the web version of this article.)

open to debate. However, since likelihoods of yield outcomes are affected by the area of the IRS on which future projections lie, and given that those projections are predominantly of warming, the negative side of temperature changes has little effect on the results.

In Finland, a typical feature associated with precipitation is early summer drought (Peltonen-Sainio et al., 2011). This is demonstrated to some extent in the results for coarse sand, although under baseline conditions water stress is found to affect yields more often closer to maturity in the model simulations. Modelled yields for the default clay loam soil are rarely affected by water stress, even for a 15% reduction in precipitation. It follows that there are limited gains to be realised with added moisture, in contrast to simulations for coarse sand, where water stress is alleviated with increased precipitation, leading to higher yields. In part, this low sensitivity is attributable to the favourable water retention properties of clay loam, but this may also be a function of the model's simplified representation of the soil water balance (de Wit et al., 2015). That limitation of WOFOST has been addressed in some studies by coupling WOFOST with a more detailed soil moisture model to simulate such effects in greater detail (e.g. Groenendijk et al., 2016; Zhou et al., 2012). Here, the basic version of the model was thought to be suitable for demonstrating the method and to keep the computational requirements of the crop model feasible.

Modelled effects on yields of oxygen shortage due to water logging were found to be negligible for the clay loam soil under a range of plausible conditions of increased precipitation. Other effects of excessive rainfall are also known to be detrimental, such as lodging, disease infestation, increased risk of soil compaction and reduced grain quality (Alakukku et al., 2003; Carter et al., 1996; Mukula and Rantanen, 1987). These could be expected to reduce yields in wetter years under large increases in precipitation and small temperature increase, but are not captured in this analysis.

To account for seasonality in climate changes as projected by climate models, a generalised pattern across the seasonal patterns projected by individual climate models was applied to the perturbations of the baseline climate. Several options were available for approximating the seasonal pattern of climate change across multiple model projections, each offering slightly different outcomes (Fronzek et al., 2010; Vormoor et al., 2017). We employed a weighting method that was designed to be applicable in different parts of Europe (for example, it was applied in Spain by Ruiz-Ramos et al., 2018). Since seasonal

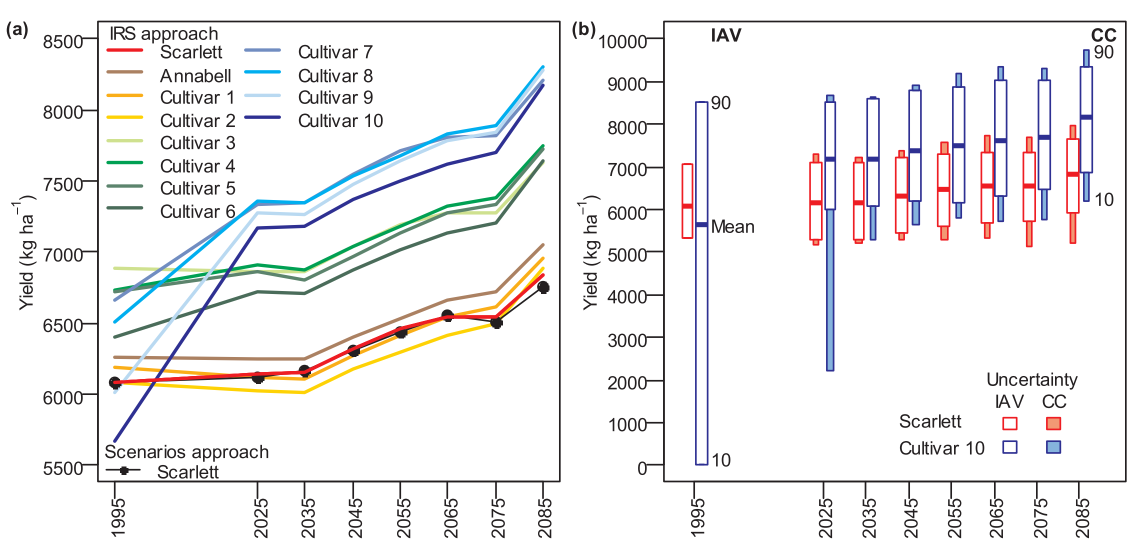

Fig. 6. Modelled barley yields (kg ha^{-1}) at 10-year intervals for 30-year time periods centred on years from 2025 to 2085 under RCP8.5: (a) 30-year means under median climate for all cultivars; (b) as in (a) for Scarlett and for Cultivar 10 (mean line within the boxes) with uncertainty expressed as the 10th and 90th percentiles of both future climate change (CC) and inter-annual variability (IAV – see sub-section 2.5). For default settings other than those specified here, see Table 1. Note that the range of the y-axis is different in the two plots. Black dots in (a) are estimates of mean yields using the scenario-based approach. (For interpretation of the colours, the reader is referred to the web version of this article.)

patterns of projected change vary across Europe, a generic method can result in patterns that may not fully replicate the local seasonal response, though the main features are captured well (Supplement 4).

The slight underestimation of the likelihood of mean yield shortfall for the IRS-based approach (with seasonal changes) as compared to the results for the scenario-based approach (Fig. 4) reflects the difference between applying a generalised pattern of seasonal changes as opposed to accounting for the full uncertainty of seasonal differences represented by the ensemble of climate change projections. The scenario-based approach estimates the likelihood as the proportion of years with yield shortfall based on simulations for all years and all members of the ensemble of GCM-based projections, each employing a different seasonal pattern of changes. This imparts more variability in yield response and more likelihood of yield shortfall, than the conservative IRS-based approach that computes annual yields during construction of the IRS but for a fixed seasonal pattern of changes. Here, likelihoods are estimated as the proportion of 30-year mean yields (interpolated from the IRS for each climate projection) falling below the threshold. Hence, differences in likelihoods can occur even if the overall mean yield across multiple scenario simulations is little different from the median yield estimated from the IRS across individual ensemble projections (black dots versus red line, respectively, for Scarlett in Fig. 6a). Nonetheless, the overall comparison suggests that the simplified methods of the IRS-based approach introduce only minor biases in estimates of impact likelihoods, and the approach offers a credible alternative to the more demanding approaches required for the scenario-based approach.

4.2. Yield likelihoods and efficacy of potential adaptation options

4.2.1. Sowing date adjustment

We applied a temperature-based sowing date estimation method similar to methods applied in other studies (e.g. Carter and Saarikko, 1996; Olesen et al., 2012) to represent autonomous adaptation. In reality, the time of sowing is governed by complex interactions between the weather, soil characteristics and other non-physical factors associated with farming decisions. However, a simple method offering a reasonable approximation of the sowing date under varying climate conditions, such as the one applied in this study, may often prove to be more practical than applying data intensive methods based on additional determinants. This view is supported by an earlier study for barley at the same location, which found that the inclusion of soil moisture conditions affected the time of sowing in only a few cases (Rötter et al., 2011). The estimated sowing dates were found to be on average 3 weeks earlier in 2085 for RCP8.5 than under the baseline. This concurs with other projections for Finland using a method that identifies the timing of temperature conditions projected for the same period under the SRES A2 (similarly high emissions) scenario that correspond to temperatures observed at sowing during 1971–2000 (Peltonen-Sainio et al., 2009a). It should be noted that the parameter values selected for the temperature-based model remain to be verified using more precise, geo-located paired sowing date and temperature observations than were available for this study. Moreover, while the method provides reasonable approximations, on average, estimates in individual years can still differ quite a lot from observations.

The adjusted sowing dates resulted in reduced likelihoods of yield shortfall compared to assuming unchanged baseline dates. Benefits of earlier sowing are primarily associated with better timing of critical growth phases in relation to the period when growth determining factors are potentially at their most ideal. Under different levels of warming and for cultivars with different rates of development, the grain filling period (anthesis to maturity) for baseline sowing occurs when radiation levels are starting to decrease (Fig. 7). This is unavoidable under baseline conditions in northern Europe, where temperature is the primary growth limiting factor and crop growth is timed to make the most of the warmest conditions, which lag peak radiation levels (Peltonen-Sainio et al., 2009b).

With warming, by sowing earlier the grain filling period coincides on average better with the time when most radiation is available during clear days (e.g. compare the right hand segments of the thick red lines for Scarlett in Fig. 7). Nonetheless, adapted sowing alone cannot fully exploit the changing conditions. This can be achieved only in combination with longer duration cultivars. For example, in Fig. 7 the benefits of a longer duration of grain filling are apparent when comparing yields in 2085 for Cultivar 7 with those of Scarlett for adapted sowing (see also Rötter et al., 2011).

4.2.2. Cultivars with higher temperature requirements

Earliness has been the principal trait in past breeding programs for adapting crops to northern conditions that exhibit short but intense growing seasons with long days (Peltonen-Sainio and Karjalainen, 1991). However, with a prolonged growing season projected under climate change, slower developing cultivars may avoid the adverse effects of warming whilst benefiting from the longer time available for crop cultivation.

The determining factor for the clustering of cultivars in their response with respect to likelihoods of shortfall and average yields (Figs. 5 and 6) was found to be the temperature sum during the reproductive phase, between anthesis and maturity (TSUM2). Higher temperature requirements for the reproductive phase corresponded with higher yields and a lower likelihood of yield shortfall. With respect to TSUM1 (emergence to anthesis) a lower temperature requirement was found to be beneficial, though the effect on the results was much weaker than that of TSUM2, even though the range of values tested was fairly wide. Both findings are consistent with those of Tao et al. (2017) for the same crop and location, where a longer reproductive phase and shorter pre-anthesis phase were found to be among the most effective traits in high-performing barley cultivars under projected changes in climate.

One possible explanation for a lower TSUM1 being advantageous under warming is again the timing of critical growth phases. A higher TSUM1 shifts the generative pre-anthesis phase to the period with the longest days, high radiation potential and increasing temperatures (Fig. 7). Under such conditions, growth is intense and development rate hastened, which may be associated with yield penalties during pre-anthesis (Peltonen-Sainio and Rajala, 2007). On the other hand, a higher TSUM2 extends the grain filling period, leading to higher yield potential as assimilation during grain filling translates directly into grain yield (Olesen et al., 2012).

With respect to the year-to-year reliability (i.e. stability of yields with respect to prior expectations), under baseline conditions the faster developing cultivars like Scarlett outperform the highest yielding cultivars such as Cultivar 10. Due to its longer growing period, Cultivar 10 fails to reach maturity in time for harvest during colder years causing crop failure. The results suggest that under baseline climate, switching to cultivars with moderately higher temperature requirements (Cultivars 3–6), were they available, might already be beneficial as the mean yields are higher and likelihoods of yield shortfall lower than for the currently cultivated cultivars (Scarlett and Annabell). Then, from 2035 onwards, the cultivars with the longest growing periods would seem to offer the highest and most stable yields.

Several other key genetic traits would need to be considered by plant breeders related to aspects such as photosynthesis (e.g. radiation use efficiency and maximum assimilation rate) and grain formation (e.g. grain number and harvest index – Tao et al., 2017). Breeding would also need to consider the potentially detrimental effects of excess water during crop development and at harvest. There is a clear imperative for close collaboration involving crop modellers, breeders, agronomists and molecular biologists, in order to achieve the common goal of designing and delivering climate resilient cultivars (Rötter et al., 2015).

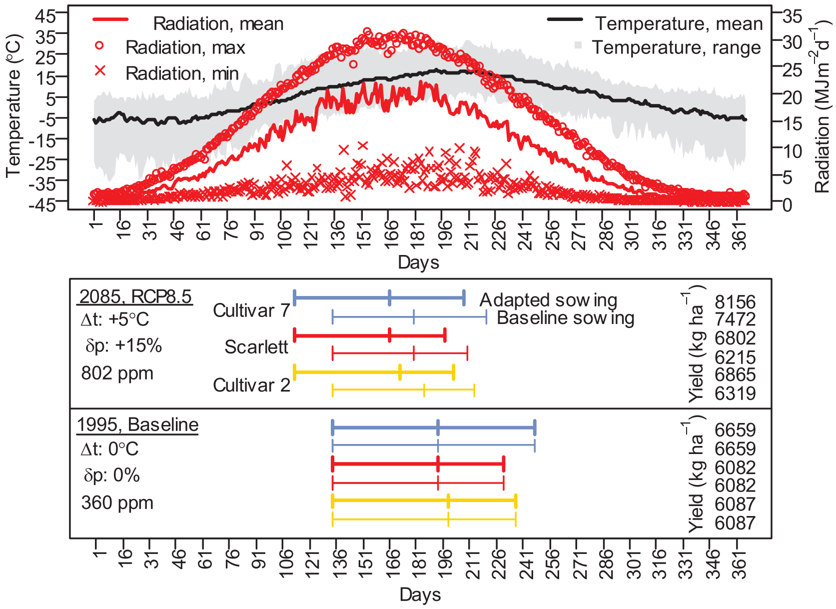

Fig. 7. Top panel: Daily long-term (1981–2010) mean (solid red line), maximum (max; red circles) and minimum (min; red crosses) radiation and temperature (solid black line) with its absolute range (grey shading). Bottom panel: Duration of growth from sowing through anthesis to harvest (solid lines with tick marks at respective stages) with adapted (thick) and baseline (thin) sowing for Scarlett (red) and Cultivars 2 (yellow) and 7 (light blue) under baseline [CO_2] and climate (lower plot) and for projected [CO_2] and median climate change under RCP8.5 for 2085 (upper plot). Corresponding yields are listed to the right. Note that duration of growth is unaffected by [CO_2]. Compared to Scarlett, Cultivar 2 has the same TSUM2 and larger TSUM1; Cultivar 7 the same TSUM1 and larger TSUM 2 (cf. Table 2). For default settings other than those specified here, see Table 1. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

4.2.3. Scenario responses

Simulations were performed for two RCPs, 4.5 and 8.5, associated with different levels of temperature and precipitation changes and [CO_2] throughout the century. Changes in climate are more severe for RCP8.5 than for RCP4.5, implying that yields would be more adversely affected. However, the increased [CO_2] is more effective at compensating for yield losses under RCP8.5 than under RCP4.5, a similar result to that reported globally for C3 crops by Levis et al. (2018). It is worth noting that assimilation is modelled as a linear function of [CO_2] in the model, although some evidence suggests that responses may level off at higher [CO_2] (Olesen and Bindi, 2002). However, the parameter values of the response to [CO_2] used in this study are conservative, based on free air carbon dioxide enrichment (FACE) experiments that show lower responses than earlier pot and chamber experiments (e.g. Long et al., 2006; Weigel and Manderscheid, 2012). Moreover, the strong response at high levels of [CO_2] presumes that adequate nitrogen is available to sustain the increased assimilation (Ainsworth and Long, 2005). Finally, it should be noted that the marked effect on the likelihood of mean yield shortfall through inclusion of [CO_2] effects is very much threshold specific. For example, for a threshold of 5000 kg ha^{-1} the likelihood of shortfall would be zero with or without elevated [CO_2] until 2065, after which it would gradually increase to 28% when not including [CO_2] (not shown).

4.3. Utility of the approach for evaluating yield likelihoods

The study has demonstrated how probabilistic representations of changes in temperature and precipitation can be applied in combination with IRS plots to estimate likelihoods of yield outcomes. As IRSs explore model sensitivities across a wide range of changes in climatic conditions, it would also be possible to estimate impacts for any new climate change projection (assuming that it falls within the range), by overlaying the existing IRSs with the new projection. In fact the approach has earlier been referred to as a “scenario-neutral” approach (Prudhomme et al., 2010). Thus, as long as [CO_2] does not exceed the range already explored, no new simulations with the impact model would be needed.

The choice of impact threshold for estimating likelihoods should be carefully considered. For practical purposes, it should be based on well-established criteria, ideally defined by and of relevance to stakeholders. In this study, the focus was on assessing and illustrating the performance of alternative cultivars. By choosing a very low threshold, all cultivars would have zero risk throughout the century making interpretations about different cultivars impossible. Our choice of the present-day average yield (6000 kg ha^{-1}) offered a meaningful threshold that also permitted useful likelihood comparisons. The choice also recognises that farm yields are typically lower than those simulated here and also lower than official variety trials (cf. Fig. 2). It hence presumes that the direction of simulated responses would also apply to farm yields. More detailed studies could examine this assumption – for example, would modelled yield responses to elevated [CO_2] based on field experiments resemble those expected under typical farm-level management?

The two-dimensional nature of the IRS plot is clearly a simplification of reality. It requires assumptions about how other relevant explanatory variables should be related to the two perturbed variables. As such, the use of the method may be limited with impact models where the response is critically dependant on more than two input variables. Conducting a sensitivity analysis with respect to multiple impact variables, though it can be achieved with present-day computers, increases the number of required simulations exponentially and greatly complicates visualisation and interpretation if responses are plotted in multi-dimensional space. Nonetheless, a scenario-neutral approach for presenting crop responses to common variables such as temperature and precipitation can also be very useful for comparison across studies and regions (Fronzek et al., 2018b), as is often required in international assessments such as for the IPCC.

Finally, the IRS-based approach is an effective way of communicating results. For example, the sequence of IRSs plots combined with climate projections can be shown as an animation alongside the evolving likelihood curve. This demonstrates how the IRS changes over time, how climate projections and their uncertainties shift to a different region of the IRS, and how this can be translated to a likelihood estimation when related to a threshold. An example animation is available and accompanies the electronic version of this manuscript (Video 1). To access the animation, simply click on the image visible below (online version only).

5. Conclusions

Likelihoods of specified barley yield impacts during the 21st century were assessed using an approach combining impact response surfaces (IRSs) of modelled yield sensitivities to changes in temperature and precipitation with probabilistic projections of future changes in the same two variables. Whilst the incremental and scenario-neutral IRS-based approach simplifies the temporal and cross-variable complexities of projected climate, it was found to offer a close approximation of likelihoods of impacts compared to results applying a more conventional and computationally-intensive scenario-based approach using ensemble GCM projections. Recognising the limitations and uncertainties associated with the application of a single crop model, four key messages emerged from the study:

1 Modelled barley yields in south-western Finland are more sensitive to temperature than precipitation changes over plausible projection ranges, with both cooling and warming leading to reductions in yields. The beneficial effects of elevated [CO_2] on yields are greater under the strongest mean changes in climate.
2 With autonomous adaptation, simulated by using earlier sowing dates, the likelihood of yield shortfall is lowered due to better timing of critical yield determining growth phases with respect to seasonal radiation and other growing conditions.
3 Simulations indicated that cultivars bred to combine short pre-anthesis and long post-anthesis phases would produce the highest yields and smallest likelihoods of yield shortfall under future scenarios assuming earlier sowing.
4 Although projected warming under RCP4.5 is more moderate than for RCP8.5, its evolving [CO_2] levels are also lower and fail to compensate fully for yield losses due to warming, raising the likelihood of yield shortfall from mid-century onwards, whereas under RCP8.5 the likelihood of yield shortfall falls to zero over the same period.

In order to refine estimates of yield impact likelihoods, some promising avenues for future research include:

- paying more attention to individual years, during which the response may differ markedly from the mean, and may further be affected by future variability change;
- improving the representation of the soil water balance possibly through coupling WOFOST with a more detailed soil moisture model than the current one-layer tipping bucket model;
- computing likelihoods with the IRS-based approach using an ensemble of different crop models, to account for inter-model uncertainties in the specification of key processes;
- spatialising the evaluation of likelihoods of yield impacts by extending the analysis from a site to a grid;
- relating the likelihood estimations to stakeholder-relevant thresholds for better applicability of the results.

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Declarations of interest

None.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.agrformet.2018.10.006.

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