Forecasting future crop suitability with microclimate data

A.S. Gardner [a,*], I.M.D. Maclean [a], K.J. Gaston [a], L. Bütikofer [a,b]

[a] *Environment and Sustainability Institute, University of Exeter, Penryn, Cornwall TR10 9FE, United Kingdom*
[b] *Sustainable Agriculture Sciences, Rothamsted Research, Harpenden, Hertfordshire AL5 2JQ, United Kingdom*

A B S T R A C T

Context: Against a background of unprecedented climate change, humanity faces the challenge of how to increase global food production without compromising the natural environment. Crop suitability models can indicate the best locations to grow different crops and, in doing so, support efficient use of land to leave space for, or share space with, nature. However, challenges in downscaling the climate data needed to drive these models to make predictions for the future has meant that they are often run using national or regional climate projections. At finer spatial scales, variation in climate conditions can have a substantial influence on yield and so the continued use of coarse resolution climate data risks maladaptive agricultural decisions. Opportunities to grow novel crops, for which knowledge of local variation in microclimate may be critical, may be missed.
Objective: We demonstrate how microclimate information can be acquired for a region and used to run a mechanistic crop suitability model under present day and possible future climate scenarios.
Methods: We use microclimate modelling techniques to generate 100 m spatial resolution climate datasets for the south-west of the UK for present day (2012–2017) and predicted future (2042–2047) time periods. We use these data to run the mechanistic crop model WOrld FOod STudies (WOFOST) for 56 crop varieties, which returns information on maximum crop yields for each planting month.
Results and conclusions: Over short distances, we find that the highest attainable yields vary substantially and discuss how these differences mean that field-level assessments of climate suitability could support land-use decisions, enabling food production whilst protecting biodiversity.
Significance: We provide code for running WOFOST in the WofostR R package, thus enabling integration with microclimate models and meaning that our methodology could be applied anywhere in the world. As such, we make available to anyone the tools to predict climate suitability for crops at high spatial resolution for both present day and possible future climate scenarios.

1. Introduction

Producing enough food to feed our growing population will be a major challenge faced by humanity over the course of this century. However, over the same period that food production must increase to meet demand, unprecedented climate change is also expected, and this may have significant consequences for agricultural output. Indeed, many studies that have projected yields under future climate scenarios predict significant losses in production for major crops (e.g. Challinor et al., 2014). If we cannot increase agricultural productivity on the land already under cultivation, natural habitat, and the biodiversity it supports, will be lost (Kehoe et al., 2017; Laurance et al., 2014). The ability accurately to predict crop suitability under present and future climates is therefore an important and timely goal, which could lead to agricultural

decisions that support global food security and aid nature conservation.

Crop suitability can be computed using a correlative approach (e.g. Arenas-Castro et al., 2020), whereby a statistical relationship between the presence or absence of a crop in a given location and the climate of that area is established and then extrapolated to predict suitability in a new climatic environment, which may be spatial and/or temporal in its novelty (Elith and Leathwick, 2009). Whilst correlative models are easy to run and can be applied at a global scale (e.g. Narouei-Khandan et al., 2016), their reliability is reduced by the fact that correlations between the predictive variables used to train the model and the physiological response of the crop (which ultimately determines where it can grow) may be indirect (Austin, 2002), such that other, unquantified factors may also be influencing the model's output (Dormann et al., 2012; Gaston, 2003; Sax et al., 2013). Away from the time and place from

which initial correlations are drawn, these 'distal' predictor variables cannot be assumed to correspond in the same way to climatically viable space and this may lead to unreliable assessments of suitability.

Mechanistic models offer an alternative approach. They use climate variables that are known to affect crop physiology to assess how changes in these might influence biological processes, such as growth and nutrient and carbon dynamics (e.g. Holzkämper, 2017; Jones et al., 2003). Some mechanistic crop models even simulate these processes over the crop's growing cycle, enabling accurate estimations of yield and an indication of the best planting and harvest dates, in reflection of the climatic suitability of an area. The physiological basis of mechanistic models means that they are generally considered more reliable when applied to new environments, including possible future climate scenarios (e.g. Guisan and Zimmermann, 2000). As well as their potential application to study the response of wild species to climate change (Kearney and Porter, 2009), they may therefore be a better choice of model for addressing problems of future food production (Estes et al., 2013) as reliable crop suitability assessments will support the optimisation of crop choice based on the climate of an area (e.g. Kadiyala et al., 2015).

Despite the benefits of mechanistic models, the climate data they require as inputs are often unavailable at high spatial resolution (Estes et al., 2013). At coarse scales, however, local variation in climate can be lost and the use of low spatial resolution data in models can therefore reduce their predictive accuracy (Early and Sax, 2011). Indeed, increasing the availability of microclimate data has been identified as crucial for improving assessments of climate suitability for crops (Challinor et al., 2018). If we can mechanistically model crop suitability at the farm- and field-scale, we might hope to make good agricultural decisions. If this helps to maximise yields, we might save additional land from conversion to agricultural production and therefore protect natural habitats. Equally, opportunities for 'land sharing' might be identified; large areas of land would remain cultivated, but with less intensive practices, like organic farming. Additionally, a diversity of crops could be grown to suit microclimates within and between fields and provide a more biodiversity-friendly agricultural matrix (Grass et al., 2019). In both cases, informed agricultural decisions that help to 'spare' or 'share' farmed land could support a sustainable increase in agricultural output by reducing conflicts between agriculture and natural ecosystems (e.g. Alkimim et al., 2015; Grass et al., 2019).

Recent advances in microclimate modelling (Lembrechts and Lenoir, 2020) provide new options to gain the climate variables necessary to run mechanistic climate suitability models over entire regions. Importantly, probabilistic projections of future weather from General Circulation Models (GCMs) can now be coupled to microclimate models to generate hourly simulations of future climate at high spatial resolution (e.g. Maclean, 2020). With these data, aspirations to run mechanistic models at high temporal and spatial resolution for the present day and for future climate change scenarios can be realised.

In this study, we demonstrate the application of microclimate modelling techniques across a region to generate the data to run the mechanistic crop model WOrld FOod STudies (WOFOST) under current and possible future climate conditions. WOFOST simulates daily growth and production of annual field crops based on knowledge about the crop, weather, and crop management (e.g. sowing date). It is employed by the Monitoring Agricultural ResourceS (MARS) project to provide monthly crop yield forecasts for European countries (van der Velde et al., 2019) and with over 25 years of use, calibration and improvement, it is considered a reliable and well-tested mechanistic crop model. To provide better integration with the microclimate model, an R implementation of WOFOST was written and successfully tested with the official testing sets (de Wit et al., 2019). This code is available as R package WofostR on https://github.com/lucabutikofer/WofostR, and includes functions to implement the crop suitability analysis described in this paper.

As microclimate models can now be applied anywhere on earth

(Kearney et al., 2020), our methodology could be followed to run WOFOST or to construct the climate variables required by other mechanistic crop models at high spatial resolution for current and future climates for any location globally. This could support reliable predictions about how climate change might affect crop suitability and lead to agricultural systems that balance the provision of food security with the need to conserve biodiversity, both now and in the future.

2. Materials and methods

2.1. Study area

We focussed on Cornwall and the Isles of Scilly in south-west England (Fig. 1a) as a case study. The region provides an interesting study system as the climate has warmed in recent years and the economy is highly dependent on farming (Kosanic et al., 2014). A strong maritime influence means that intra-annual fluctuations in temperature are lower than for many other places in the UK and with future climate warming some areas of agricultural land are likely to be among the first in the UK that become frost-free throughout the year (Met Office, 2016). Absence of frost is an important physiological threshold for plant growth and development (Inouye, 2000) and frost-free status could enable diversification of agriculture to grow higher value, novel crops originating from warmer regions. Mechanistically modelling crop suitability using microclimate data would contribute to identifying where such opportunities might be realised.

The WOFOST model requires daily climate values of mean vapour pressure, wind speed and precipitation, total incoming shortwave radiation, and minimum and maximum temperature. We calculated these variables for current (2012–2017) and predicted future (2042–2047) climate conditions using functions in the R package *microclima* (Maclean et al., 2019) as follows.

2.2. Current climate data

For the years 2012–2017 we downloaded the following climate data and extracted values for our study site:

1. Daily minimum and maximum temperature at 1 km grid resolution from the UK Met Office (Met Office, 2018);
2. Six-hourly sea-level pressure, wind speed and wind direction, and specific humidity available at ~2° grid resolution from the National Weather Surface National Centres for Environmental Prediction (NOAA-NCEP; Kalnay et al., 1996);
3. Hourly surface incoming shortwave (SIS), and direct normal (DNI) radiation and cloud fractional cover available at 0.05° grid resolution from the EUMETSAT Satellite Application Facility on Climate Monitoring (CMSAF; Posselt et al., 2014); and
4. Daily mean sea surface temperatures at a grid resolution of 0.25° from the National Oceanic and Atmospheric Administration (NOAA; Reynolds et al., 2007).

We interpolated six-hourly specific humidity and pressure data and daily sea-surface temperature data to hourly using the native *spline* function of R (R Core Team, 2019). Easterly and northerly wind vectors were derived from wind speed and wind direction, which were spline interpolated to hourly before back-calculating hourly wind speed and wind direction. Wind speed at 1 m height above the ground was calculated using the *microclima::windcoef* function, which applies a topographic shelter coefficient, using elevation, to wind data. Elevation data were sourced using the *microclima::get_dem* function.

Radiation values at low horizon values and for missing data were derived by interpolation. We then calculated hourly diffuse radiation from hourly incoming shortwave radiation and direct normal radiation multiplied by the solar index. We used values for direct and diffuse radiation as well as the hourly humidity and pressure and daily maximum
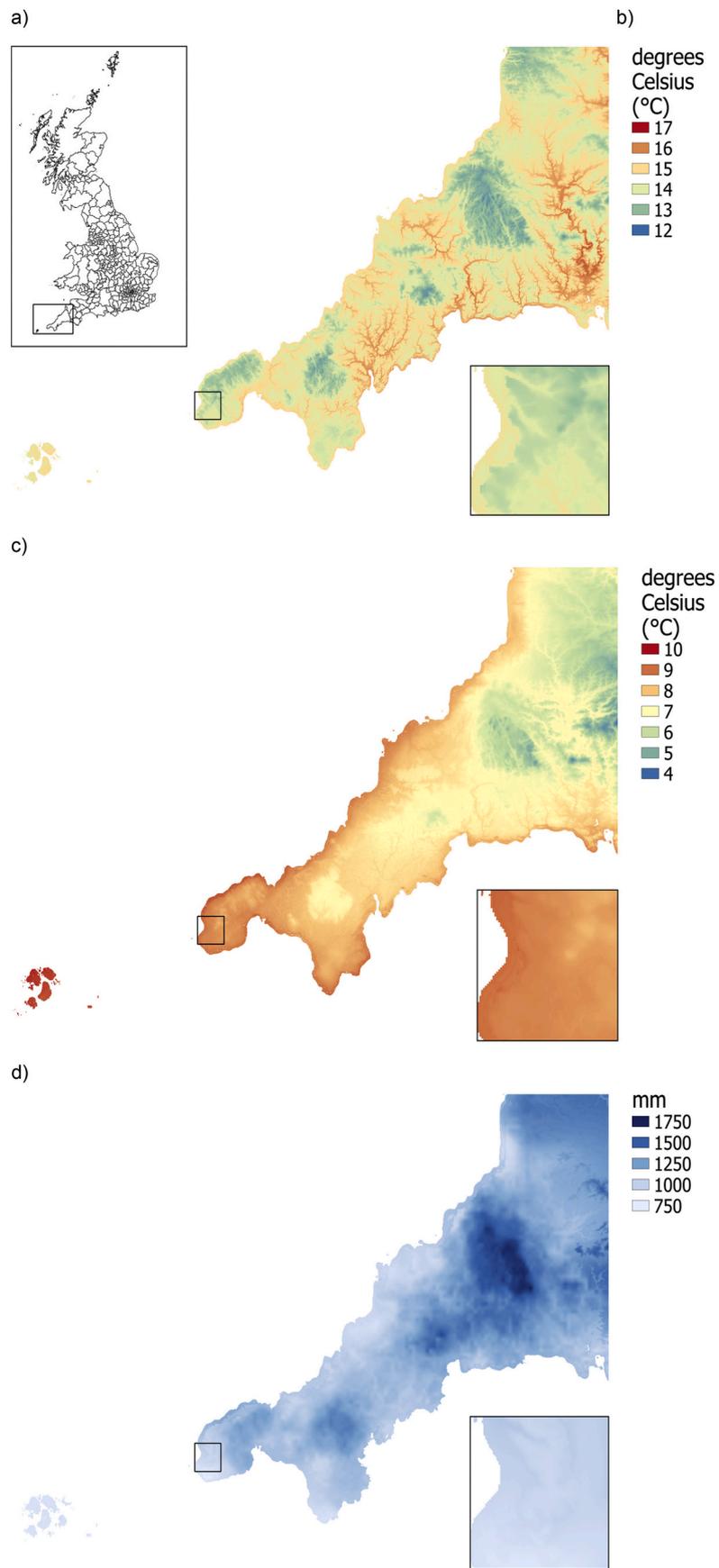
Fig. 1. Location of the study area in the UK (a), Spatial variation in mean maximum daily temperature (°C) (b), mean minimum daily temperature (°C) (c) and total annual precipitation (mm) (d). All climate data are averages for the period 2012–2017 at 100 m spatial resolution. The size of the area shown in inset is 5km².

and minimum temperature data to derive hourly temperature with the *microclima::hourlytemp* function. We calculated shortwave radiation and net longwave radiation using the *microclima::shortwavetopo* and *microclima::longwavetopo* functions, respectively, and final values of net radiation were shortwave minus longwave radiation values.

We determined mesoclimate effects by fitting a thin-plate spline model to the hourly differences between land and sea temperature data with coastal exposure and elevation as covariates. We applied this model to derive land-sea temperature differentials using predictor variables resampled to 100 m spatial resolution. Temperature was then further adjusted to account for expected differences due to cold air drainage effects. Cold air drainage potential (binary: 1 = Yes, 0 = No) was calculated using the *microclima::cadconditions* function.

Model coefficients were derived automatically by microclima using procedures described in Kearney et al. (2020). We then ran *microclima::runmicro* which calculates temperature anomalies due to radiation and wind. Hourly temperatures were derived by addition of this anomaly to the hourly temperature values from the mesoclimate model. To preserve spatial variability whilst removing systematic bias in fine-scale temperature estimates compared to coarse resolution data, we applied a correction factor to the outputs of the microclimate model. We sampled 7560 cells for each hour from the high-resolution dataset and calculated their mean values. We subtracted the difference between these values and the corresponding mean hourly temperature from the coarse resolution climate dataset from the fine-scale dataset.

We calculated hourly vapour pressure using the *microclima::humidityconvert* function and then derived daily means. Daily global radiation and windspeed were also calculated from the mean of all hourly values for each day. Minimum and maximum daily temperatures were determined from the minimum and maximum hourly values for each 24-h period.

Precipitation data were retained as a daily variable. We resampled precipitation values to 100 m spatial resolution and applied a thin plate spline model with elevation as a covariate to derive final daily precipitation values.

The microclimate model has been well-validated using field observations, details of which are provided in Maclean et al. (2017, 2019) and Maclean (2020). In summary, the model has been validated against 233,357 temperature readings from 167 locations in Cornwall over the period 2010–2014 and 10,000 field measurements of soil moisture obtained from 250 locations in Cornwall over the period 2010–2011.

2.3. Future climate data

We obtained regional climate generator projections for 2042–2047 from the Met Office Hadley Centre (Met Office Hadley Centre, 2018). This dataset consists of 12 possible climate realisations under Representative Concentration Pathway 8.5 (RCP8.5) and provides spatially and temporally coherent, gridded climate variable datasets at 12 km spatial resolution. Each projection is a plausible example of daily weather under global warming and can be mechanistically downscaled for crop suitability modelling.

We downloaded minimum air temperature, maximum air temperature, eastward wind component, northward wind component, net surface longwave flux, net surface shortwave flux, specific humidity, pressure at mean sea level and precipitation rate, and used R package *UKCP18Adjust* (https://github.com/ilyamaclean/UKCP18Adjust) to derive hourly values at 5 km spatial resolution and to correct for model biases (Maclean, 2020).

We processed climate data as described above for the current climate data, except net radiation was calculated following the methods set out in Maclean (2020). To run WOFOST for future climate we used climate data from five different GCMs (one for each year) to reduce possible biases inherent to any one GCM.

While it is not possible to validate the microclimate model for future conditions, extensive calibration and testing has confirmed successful performance over historic periods (Maclean et al., 2017, 2019). Furthermore, the microclimate model is based on universal physical laws of energy and vapour exchange, which show no evidence of change over historic periods, and are not expected to change into the future.

2.4. Running the WOFOST model

The WOFOST algorithm computes the accumulation and partitioning of biomass in a crop from first principles given daily weather parameters and soil characteristics. 56 parameterised crop varieties are sourced by the WofostR package from the Python Crop Simulation Environment repository (https://github.com/ajwdewit/WOFOST_crop_parameters). Multiple varieties of the same crop account for, inter alia, differences in development times and time taken to reach maturity given the same pedoclimatic conditions. Maize, for example, has six varieties, each of which has different values for both the temperature sum required for the development from emergence to anthesis and from anthesis to maturity. WOFOST computes daily photosynthetically active radiation and its interception by the canopy according to the climate data provided and the current value of photosynthetically active plant surface (leaves and, in some crops, stems). Carbohydrate production is calculated according to climatic, environmental, and physiological variables, and photosynthate is then partitioned to roots, stems, leaves and storage organs according to the plant development stage, which in turn depends on the accumulated growing degree days. When maturity is reached, biomass accumulated by the storage organs corresponds to the yield value. Water usage by the plant (activated by variable "waterLimited" in function *Wofost*) depends on climate, development stage, and a simple, "tipping bucket" soil model.

Weather variables were transformed to units required by WOFOST. We ran one WOFOST simulation with function *Wofost* for each month in the modelled periods (2012–2017 and 2042–2047) for each available crop variety (see *WofostR::cropVarList*). Each model was run until the crop either reached maturity or a maximum time of 365 days. Details of model parameterisation are provided in Appendix A. For each crop-variety that reached maturity the optimal sowing time was computed by averaging the Total Weight of Storage Organ (TWSO) produced across Cornwall for each sowing month. By selecting the TWSO values from the optimal sowing time, we can produce maps of the five-year average maximum obtainable yield for each crop variety that reached maturity. We consider yield values to reflect climatic suitability and discuss results for the region and for a 5km^2 area of agricultural land near Sennen Cove (50.09°N, −5.67°W), which provides a field-scale case study. We also calculate and discuss differences between the time taken to reach maturity (season length) under current and future conditions.

Since the aim of our study is to illustrate the large variability of crop suitability at fine spatial and temporal scales, rather than absolute estimates of yield or phenology, we did not perform any local calibration or validation of the WOFOST model results. In any case, farm and field-scale crop yield data are unavailable for the UK, for reasons associated with General Data Protection Regulations. Nevertheless, WOFOST's reliability in simulating crop development given a set of crop parameters is well-validated (to the extent that it forms the key component of the European Monitoring Agricultural ResourceS (MARS) crop yield forecasting system). Example validation studies from European countries include those for wheat (Boogaard et al., 2013; Castañeda-Vera et al., 2015), barley (Rötter et al., 2012), rapeseed (Gilardelli et al., 2016) and rice (Confalonieri et al., 2009). Further examples can be found on the WOFOST website (https://www.wur.nl/en/Research-Results/Research-Institutes/Environmental-Research/Facilities-Tools/Software-models-and-databases/WOFOST/Documentation-WOFOST.htm).

3. Results

3.1. Spatial variability in microclimate conditions

There was considerable spatial variation in climate conditions across the study region at 100 m spatial resolution and we present data for the current period that illustrates this below (Fig. 1). Corresponding climate maps for the future period can be found in Appendix B, Fig. B.1. Across Cornwall, mean maximum daily temperatures from 2012 to 2017 ranged from 12.4C to 17.8C and mean minimum daily temperatures ranged from 4.2C to 9.8C. Some of the driest areas, such as the low-lying Isles of Scilly, an archipelago off the west coast of Cornwall, experienced half the total annual precipitation (~750 mm/year) of the wettest places, which included Bodmin Moor, an exposed moorland to the north-west of Cornwall at 300-420 m elevation.

The climate was highly variable across short distances, including at the field-scale. The inset in Fig. 1 shows a 5km^2 area of predominantly agricultural land near Sennen Cove (50.09°N, −5.67°W). Mean maximum daily temperatures and mean minimum daily temperatures differed by 1.8C and 1C, respectively.

3.2. Current and future crop suitability

Thirty-one crops grew to physiological maturity under current climate conditions and 34 crops reached maturity under future climate conditions in at least one location (Appendix B, Table B.1). The three crops for which the climate became suitable by the period 2042–2047 were varieties of millet (*Pennisetum glaucum*), mungbean (*Vigna radiata*) and sorghum (*Sorghum bicolor*). Cowpea (*Vigna unguiculata*) was predicted to have the largest percentage increase in average yield between periods (52%), although the time taken to reach maturity (season length) was extended on average by 97 days (Fig. 2).

3.3. Spatial variability in crop suitability

Reflecting the spatial heterogeneity in microclimate conditions, maximum attainable yields for all crops varied across the study region in both periods. On average, the highest maximum yields were 1.7-times greater than the lowest maximum yields in the current period (range: 1.3–2.5). The highest maximum yields for the future period were on average 1.9-times greater than the lowest maximum yields (range: 1.2–2.8).

All crops that reached maturity under current and future climates showed both increases and decreases in suitability over time across the study area. Fig. 3 shows the five-year average maximum attainable yield across Cornwall for oilseed rape (*Brassica napus* ssp. *oleifera*) for both periods. Maximum yields across Cornwall ranged from 3.68 t/ha to 5.00 t/ha in the current period and from 3.72 t/ha to 6.03 t/ha in the future period. Percentage difference in mean yields between periods averaged 10.7% but ranged from −17.46% to +28.92%. Even within the 5km^2 area shown inset, maximum yields in the current and future periods varied by 0.4 t/ha and 0.9 t/ha respectively and percentage difference in yield between periods ranged from −7.8% to 11.1%.

The length of time taken for each crop to reach maturity also varied spatially and, in some areas, shortened season lengths might compensate for any reduction in yield from the single best planting month by permitting a second harvest. Mean soybean (*Glycine max*) yields, for example, were predicted to decline slightly between the current and future periods but it remained a viable crop in the future and the time taken to reach maturity reduced by up to 71 days (average − 25 days).

Boxplots showing average maximum yield and season lengths under present and future climates for each crop are provided in the supplementary materials (Appendix B, Fig. B.2). These data are summarised in Appendix B, Table B.2 (maximum yield) and Table B.3 (season length).

3.4. Temporal variability in crop suitability

Climate suitability for all crops varied between years. For some crops this meant that although mean yields were predicted to be lower in the future, they would become more consistent. Mean grain maize (variety 201) yields, for example, were 1.24 t/ha lower in the future period than in the current period, but the coefficient of variation in yield was predicted to reduce on average from 14.5% to 11.5% by 2042–2047 (Appendix B, Table B.4). For other crops, such as oilseed rape (*Brassica napus*), yields were expected to both increase and become more stable over time across the region. Fig. 4 shows the coefficient of variation in maximum annual yield for oilseed rape for current (2012–2017) and future (2042–2047) periods. Variation in annual yield was reduced on average by 5.8% between periods. In the 5km^2 area inset, the coefficient of variation in annual yield ranged from 5.5–8.1% (average: 6.7%) in the current period and 1.8–7.9% (average: 3.8%) in the future period.

Variation in season length showed similar trends. Summary statistics for temporal variability in maximum yields and season lengths for each crop are reported in Appendix B, Table B.4.

4. Discussion

Our study demonstrates how to obtain high spatial resolution climate data for present and future time periods for use in a mechanistic crop suitability model. We show that estimating productivity at fine spatial
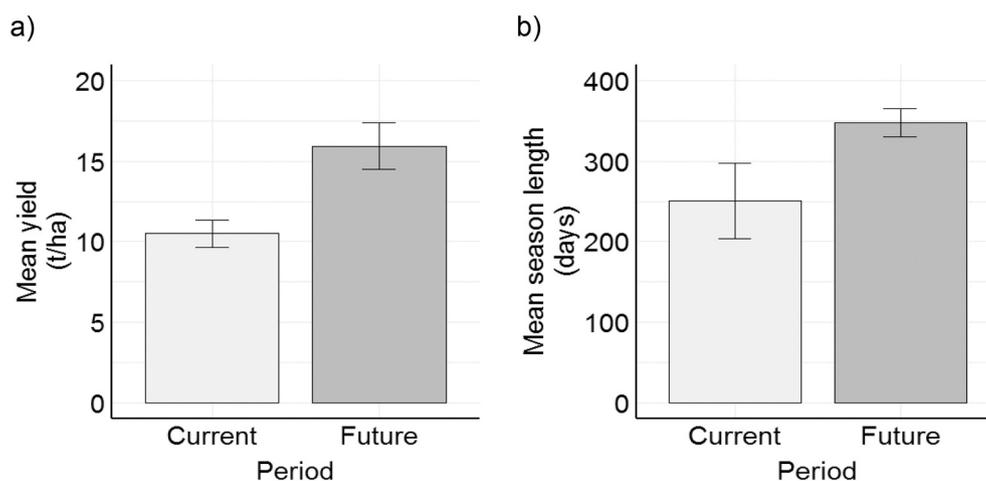
Fig. 2. Mean yield (a) and mean season length (b) for cowpea (*Vigna unguiculata*) under present (2012–2017) and future (2042–2047) climate periods. Data are summaries for the whole region with error bars representing standard deviation from the mean. Yield values are for the best planting month.
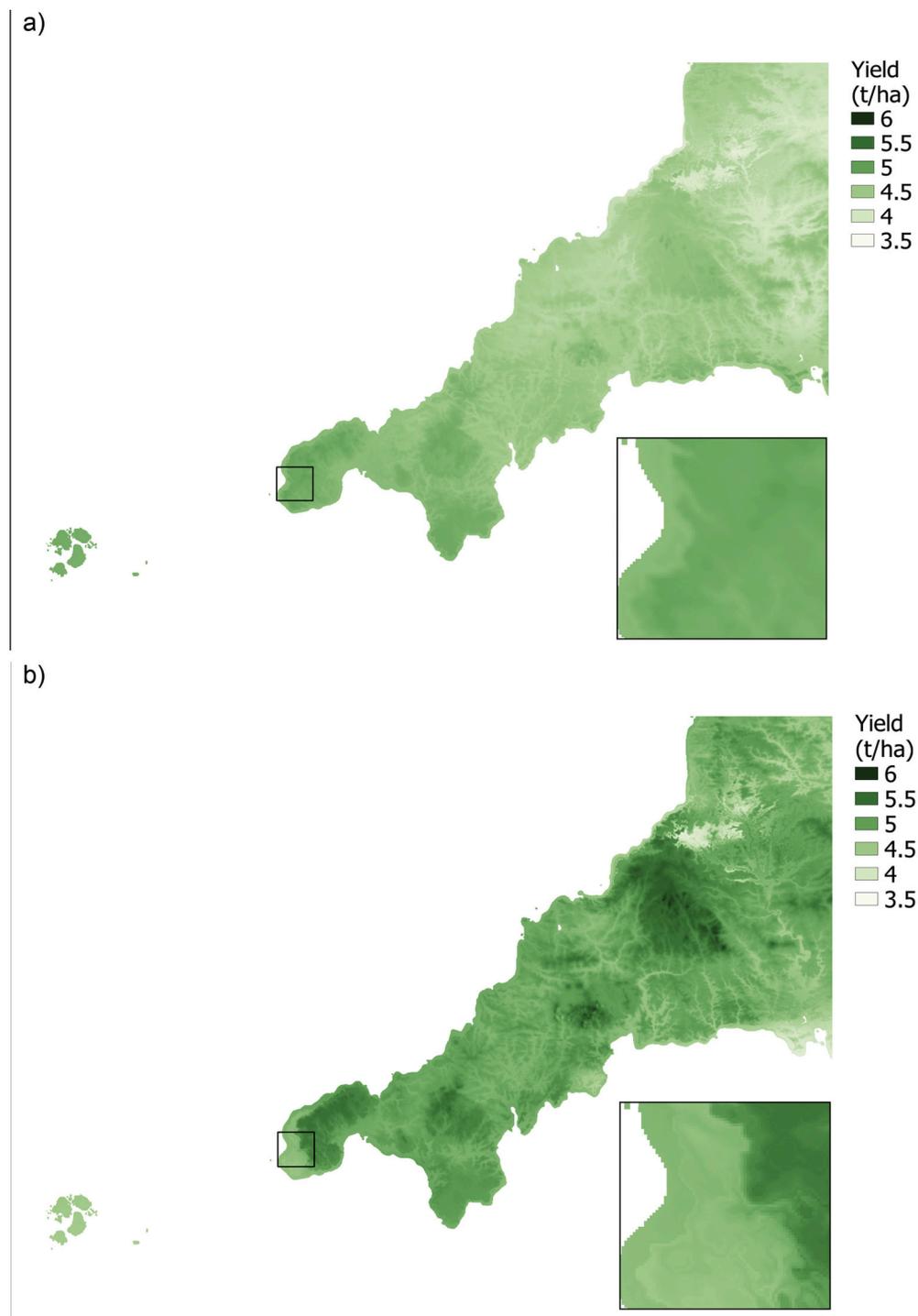
Fig. 3. Average maximum yield (t/ha) for oilseed rape (*Brassica napus*) under current (a) and future (b) climate conditions. Black square indicates location of 5km²inset.

scales can be important as, at 100 m spatial resolution, maximum yields for all crops varied substantially across short distances in both time periods, and the impacts of climate change on crop yields were also spatially heterogeneous.

Our findings support previous thinking that crop yield estimations at coarse spatial resolution may not be representative of smaller, targeted areas (Grassini et al., 2015) and so the use of microclimate data will likely increase the accuracy of these predictions. Assessing crop suitability at the farm- and field-level can also be most appropriate given that crop decisions are made often at these fine spatial scales.

By providing more accurate assessments of yield, the use of microclimate data in mechanistic crop models could support the best decisions about what crops or crop varieties to grow in different locations and this could aid the most appropriate land allocation strategies for the sustainable intensification or extensification of farming (Peltonen-Sainio et al., 2019). For example, higher-yield farming could result in land sparing, whereby intact habitat is saved from conversion to agriculture as demand can be met on current agricultural land (Balmford et al., 2005). Equally, microclimate information could be used to inform a 'land sharing' approach to biodiversity protection. Although a land

a)

b)
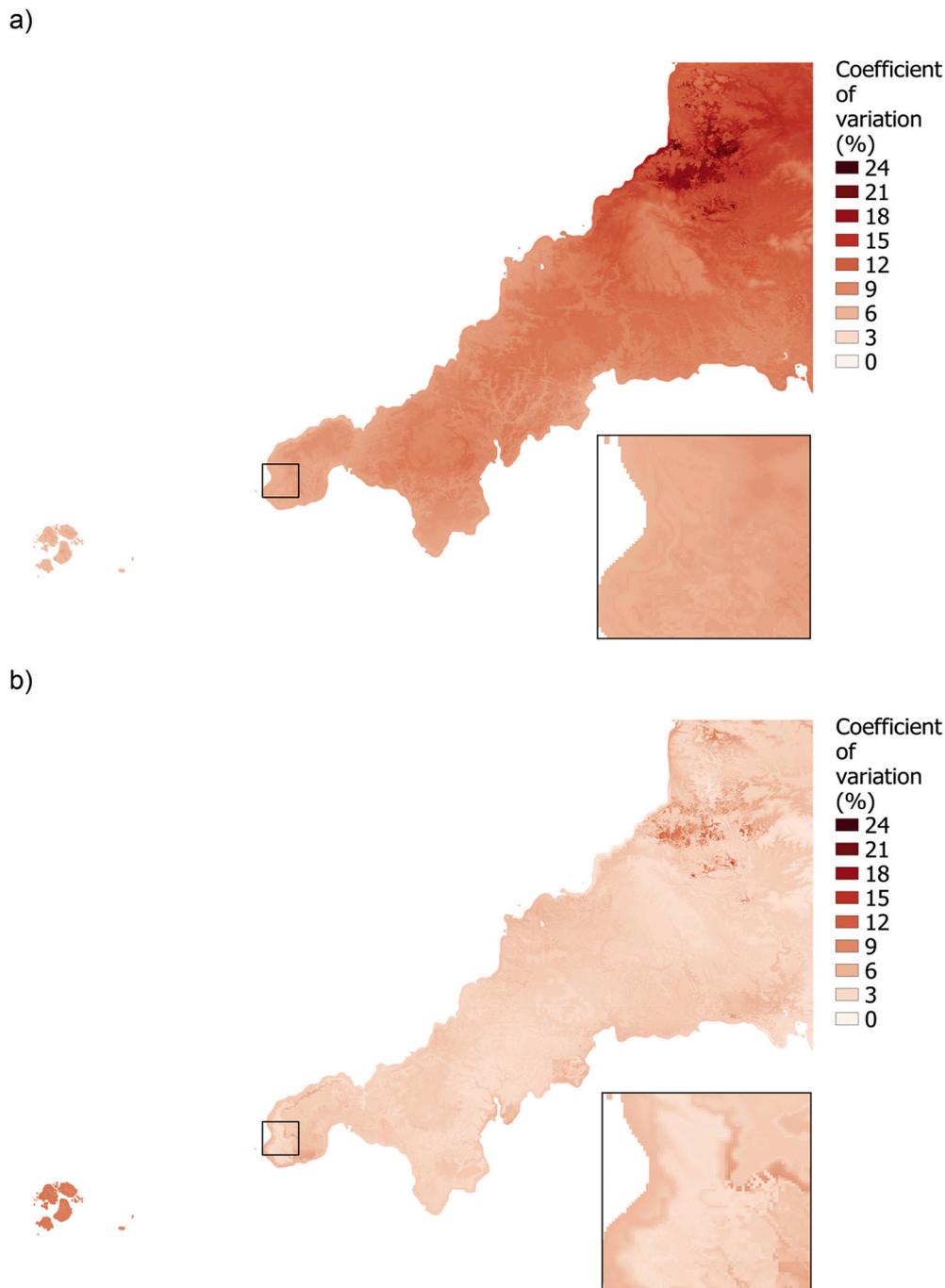
Fig. 4. Maps of coefficient of variation in maximum annual yield for oilseed rape (*Brassica napus*) for current (2012–2017) (a) and future (2042–2047) (b) climate periods. Black square indicates location of 5km^2 inset.

share approach means that large areas of land remain under cultivation, by using microclimate information to select a diversity of crops to grow across the landscape, in reflection of suitability to different microclimate conditions, agricultural matrices are created that can provide habitats for species important to ecosystem health (Grass et al., 2019).

Agricultural expansion is a leading cause of biodiversity loss globally (Phalan et al., 2016) and both land spare and land share approaches have been shown to be successful in protecting biodiversity (e.g. Wunder, 2001). Indeed, land sparing has been considered as one of the best prospects to limit the impacts of agriculture on remaining natural habitat (Brubaker, 1977; Angelsen and Kaimowitz, 1998). Whether land is spared or shared, the use of microclimate data to select and grow crops in areas to which they are well suited may reduce the need for additional

inputs (like fertiliser) to achieve profitable yields, and so support a 'wildlife friendly' agricultural system. In this way, strategic land use to maximise agricultural yields and produce more food on available land or to achieve greater diversity in the crops and varieties grown could help to meet environmental, as well as food security goals (Scherer et al., 2018). By maintaining ecological diversity alongside productive agricultural systems, we will ultimately also secure the ecosystem services (such as pest control, pollination, and soil fertility) required for farming in the future (Power, 2010). We recognise that policy interventions may be required (Rudel et al., 2009) to ensure that any increase in yield does not provide financial incentive to expand agriculture further (e.g. Angelsen et al., 1999; Ramankutty and Rhemtulla, 2012). However, without considering heterogeneity, we might fail to understand the

optimal spatial configuration of land use and miss opportunities to minimise trade-offs between agricultural production and biodiversity (Butsic et al., 2020).

More generally, the farm- and field-scale may also reflect the size of the management unit (Richards et al., 2017) and so be the most relevant scale at which to provide information that guides the development of site-specific strategies (Diker et al., 2004; Jin et al., 2017). Microclimate information could, for example, suggest the best planting dates for different crops and crop varieties, identify possible interactions between microclimate and the effects of practices such as tillage (e.g. Irmak et al., 2019), and inform the use of precision agricultural technologies both within and between fields for better control of inputs and outputs (e.g. Watthanawisuth et al., 2009). Microclimate data could therefore be a tool to aid efficient agricultural land use planning, implementation, and management to maximise yields, optimise resource use and minimise waste.

Microclimate information could also be useful to identify the best locations to trial or commit to growing novel crops. Indeed, high resolution current climate data has been used previously to identify suitable microclimates to grow wine grapes in areas with regional temperatures that are borderline 'too cool' (Dunn et al., 2019). Accordingly, vineyards in higher latitude regions are often located on equatorward-facing slopes to take advantage of the higher growing season temperatures, exposure to solar radiation and the reduced risk of frost due to topography (slope and aspect) that permit successful cultivation (Mosedale et al., 2016). Climate warming may offer opportunities to expand the cultivation of wine grapes or other more exotic crops at or beyond the northern limits of their current range (e.g. Audsley et al., 2006). Without microclimate data, however, current or future potential for crop diversification in these often small 'islands' of suitable land may be missed. As novel crops have the potential to give high returns (e.g. Parker and Abatzoglou, 2018), their cultivation may also support land sparing.

Knowledge of how yields may vary from year-to-year could prove vital to risk assessments for agricultural diversification as shifting cultivation to a new crop may require significant upfront costs by farmers and they may be unlikely to risk these investments if minimum yields cannot be assured (Parker and Abatzoglou, 2018). We found that the inter-annual variation in maximum crop yields was spatially heterogeneous across both periods, highlighting how the use of microclimate data in crop models could provide important information about where crops may deliver dependable, or at least commercially viable, harvests. Accurate predictions of yield variability could become increasingly important in the future as climate change is expected to alter both the frequency and intensity of extreme events (Stocker et al., 2013) which often have high biological relevance (Ummenhofer and Meehl, 2017) and can cause significant crop losses (Lesk et al., 2016).

Mechanistic models should by no means be considered 'perfect'. In the case of WOFOST, for example, neither soil suitability (structure and quality), nor biotic interactions between the crop and other species such as pests and pollinators, are explicitly considered. Although some non-climatic limitations might be overcome by management, such as soil augmentation or pesticide application (Yao et al., 2005), this would not be without cost to the farmer. Crop suitability could be significantly affected by socio-economic factors (e.g. Parker and Abatzoglou, 2018) and researchers should seek to incorporate these considerations into crop suitability assessments or acknowledge model limitations. Other checks might also be required. For example, through its monthly simulations, WOFOST provides crop yield estimates for each possible sowing month and from this the best planting strategy can be inferred. However, planting time suitability does not consider factors such as field conditions and whether the soil would be too waterlogged to be worked on. Thus, a user may choose to discard yield estimations from crops sown during unrealistic planting dates.

Finally, mechanistic models require knowledge of how climate influences the physiology of the crop in a way that affects its development and the quality and quantity of harvest. In the case of WOFOST, for example, crop suitability analyses are constrained to the 56 crop varieties for which parameter sets exist and are made publicly available. Without the information to parameterise other crops and crop varieties, farming opportunities may be missed. There are expert-based databases for many crops (e,g, PLANTS, USDA (https://plants.USDA.gov)), but collating physiological information for other crops and varieties or their wild relatives where it is currently lacking, and validating crop suitability models such as WOFOST against this information, will be important for the future of mechanistic models.

5. Conclusion

An ability to make accurate assessments of climatic suitability for crops will be a crucial prerequisite to predict reliably how climate change may affect agricultural production. We show how microclimate data can capture temporal and spatial variation in climate suitability that, for crops, could provide better approximation of predicted yields and inform agricultural decision-making. In this way, the use of microclimate data in crop suitability assessments could also aid the harmonisation of agricultural production with biodiversity conservation, one of the greatest sustainability challenges faced by humanity. Our methods could be applied to run WOFOST in other areas or to derive microclimate estimates for use in other mechanistic models. Thus, limitations to expand mechanistic modelling of biological responses to climatic changes no longer lie in the ability to acquire climate data at high temporal and spatial resolution, but in the knowledge of how climate influences the physiology of the target organism. With this information, it would be possible, in theory, reliably and mechanistically to model present and possible future climate suitability for any species, anywhere on earth.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.agsy.2021.103084.

References

Alkimim, A., Sparovek, G., Clarke, K.C., 2015. Converting Brazil's pastures to cropland: an alternative way to meet sugarcane demand and to spare forestlands. Appl. Geogr. 62, 75–84.

Angelsen, A., Kaimowitz, D., 1998. When does technological change in agriculture promote deforestation? In: Lee, D.R., Barrett, D.R. (Eds.), Tradeoffs or Synergies? Agricultural Intensification, Economic Development and the Environment. CABI Publishing, New York, pp. 89–114.

Angelsen, A., Shitindi, E.F.K., Aarrestad, J., 1999. Why do farmers expand their land into forests? Theories and evidence from Tanzania. Environ. Dev. Econ. 4 (3), 313–331.

Arenas-Castro, S., Gonçalves, J.F., Moreno, M., Villar, R., 2020. Projected climate changes are expected to decrease the suitability and production of olive varieties in southern Spain. Sci. Total Environ. 709, 136161.

Audsley, E., Pearn, K.R., Simota, C., Cojocaru, G., Koutsidou, E., Rounsevell, M.D.A., Alexandrov, V., 2006. What can scenario modelling tell us about future European scale agricultural land use, and what not? Environmental Science & Policy 9 (2), 148–162.

Austin, M.P., 2002. Spatial prediction of species distribution: an interface between ecological theory and statistical modelling. Ecol. Model. 157 (2–3), 101–118.

Balmford, A., Green, R.E., Scharlemann, J.P., 2005. Sparing land for nature: exploring the potential impact of changes in agricultural yield on the area needed for crop production. Glob. Chang. Biol. 11 (10), 1594–1605.

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

Brubaker, S., 1977. Land: the far horizon. Am. J. Agric. Econ. 59 (5), 1037–1044.

Butsic, V., Kuemmerle, T., Pallud, L., Helmstedt, K.J., Macchi, L., Potts, M.D., 2020. Aligning biodiversity conservation and agricultural production in heterogeneous landscapes. Ecol. Appl. 30 (3), e02057.

Castañeda-Vera, A., Leffelaar, P.A., Álvaro-Fuentes, J., Cantero-Martínez, C., Mínguez, M.I., 2015. Selecting crop models for decision making in wheat insurance. Eur. J. Agron. 68, 97–116.

Challinor, A.J., Watson, J., Lobell, D.B., Howden, S.M., Smith, D.R., Chhetri, N., 2014. A meta-analysis of crop yield under climate change and adaptation. Nat. Clim. Chang. 4 (4), 287.

Challinor, A.J., Müller, C., Asseng, S., Deva, C., Nicklin, K.J., Wallach, D., Koehler, A.K., 2018. Improving the use of crop models for risk assessment and climate change adaptation. Agricultural Systems 159, 296–306.

Confalonieri, R., Acutis, M., Bellocchi, G., Donatelli, M., 2009. Multi-metric evaluation of the models WARM, CropSyst, and WOFOST for rice. Ecol. Model. 220 (11), 1395–1410.

de Wit, A., Boogaard, H., Fumagalli, D., Janssen, S., Knapen, R., van Kraalingen, D., Supit, I., van der Wijngaart, R., van Diepen, K., 2019. 25 years of the WOFOST cropping systems model. Agric. Syst. 168, 154–167.

Diker, K., Heermann, D.F., Brodahl, M.K., 2004. Frequency analysis of yield for delineating yield response zones. Precis. Agric. 5 (5), 435–444.

Dormann, C.F., Schymanski, S.J., Cabral, J., Chuine, I., Graham, C., Hartig, F., Singer, A., 2012. Correlation and process in species distribution models: bridging a dichotomy. Journal of Biogeography 39 (12), 2119–2131.

Dunn, M., Rounsevell, M.D., Boberg, F., Clarke, E., Christensen, J., Madsen, M.S., 2019. The future potential for wine production in Scotland under high-end climate change. Reg. Environ. Chang. 19 (3), 723–732.

Early, R., Sax, D.F., 2011. Analysis of climate paths reveals potential limitations on species range shifts. Ecol. Lett. 14 (11), 1125–1133.

Elith, J., Leathwick, J.R., 2009. Species distribution models: ecological explanation and prediction across space and time. Annu. Rev. Ecol. Evol. Syst. 40, 677–697.

Estes, L.D., Bradley, B.A., Beukes, H., Hole, D.G., Lau, M., Oppenheimer, M.G., Turner, W.R., 2013. Comparing mechanistic and empirical model projections of crop suitability and productivity: implications for ecological forecasting. Global Ecology and Biogeography 22 (8), 1007–1018.

Gaston, K.J., 2003. The Structure and Dynamics of Geographic Ranges. Oxford University Press, Oxford.

Gilardelli, C., Stella, T., Frasso, N., Cappelli, G., Bregaglio, S., Chiodini, M.E., Confalonieri, R., 2016. WOFOST-GTC: A new model for the simulation of winter rapeseed production and oil quality. Field Crops Research 197, 125–132.

Grass, I., Loos, J., Baensch, S., Batáry, P., Librán-Embid, F., Ficiciyan, A., Udy, K., 2019. Land-sharing/-sparing connectivity landscapes for ecosystem services and biodiversity conservation. People Nat. 1 (2), 262–272.

Grassini, P., van Bussel, L.G., Van Wart, J., Wolf, J., Claessens, L., Yang, H., Cassman, K. G., 2015. How good is good enough? Data requirements for reliable crop yield simulations and yield-gap analysis. Field Crops Research 177, 49–63.

Guisan, A., Zimmermann, N.E., 2000. Predictive habitat distribution models in ecology. Ecol. Model. 135 (2–3), 147–186.

Holzkämper, A., 2017. Adapting agricultural production systems to climate change—what's the use of models? Agriculture 7 (10), 86.

Inouye, D.W., 2000. The ecological and evolutionary significance of frost in the context of climate change. Ecol. Lett. 3 (5), 457–463.

Irmak, S., Kukal, M.S., Mohammed, A.T., Djaman, K., 2019. Disk-till vs. no-till maize evapotranspiration, microclimate, grain yield, production functions and water productivity. Agric. Water Manag. 216, 177–195.

Jin, Z., Azzari, G., Lobell, D.B., 2017. Improving the accuracy of satellite-based high-resolution yield estimation: a test of multiple scalable approaches. Agric. For. Meteorol. 247, 207–220.

Jones, J.W., Hoogenboom, G., Porter, C.H., Boote, K.J., Batchelor, W.D., Hunt, L.A., Wilkens, P.W., Singh, U., Gijsman, A.J., Ritchie, J.T., 2003. The DSSAT cropping system model. Eur. J. Agron. 18 (2–3), 235–265.

Kadiyala, M.D.M., Nedumaran, S., Singh, P., Chukka, S., Irshad, M.A., Bantilan, M.C.S., 2015. An integrated crop model and GIS decision support system for assisting agronomic decision making under climate change. Sci. Total Environ. 521-522, 123–134.

Kalnay, E., Kanamitsu, M., Kistler, R., Collins, W., Deaven, D., Gandin, L., Zhu, Y., 1996. The NCEP/NCAR 40-year reanalysis project. Bulletin of the American Meteorological Society 77 (3), 437–472.

Kearney, M., Porter, W., 2009. Mechanistic niche modelling: combining physiological and spatial data to predict species' ranges. Ecol. Lett. 12 (4), 334–350.

Kearney, M.R., Gillingham, P.K., Bramer, I., Duffy, J.P., Maclean, I.M., 2020. A method for computing hourly, historical, terrain-corrected microclimate anywhere on earth. Methods Ecol. Evol. 11 (1), 38–43.

Kehoe, L., Romero-Muñoz, A., Polaina, E., Estes, L., Kreft, H., Kuemmerle, T., 2017. Biodiversity at risk under future cropland expansion and intensification. Nat. Ecol. Evol. 1 (8), 1129–1135.

Kosanic, A., Harrison, S., Anderson, K., Kavcic, I., 2014. Present and historical climate variability in south West England. Clim. Chang. 124 (1–2), 221–237.

Laurance, W.F., Sayer, J., Cassman, K.G., 2014. Agricultural expansion and its impacts on tropical nature. Trends Ecol. Evol. 29 (2), 107–116.

Lembrechts, J.J., Lenoir, J., 2020. Microclimatic conditions anywhere at any time! Glob. Chang. Biol. 26 (2), 337–339.

Lesk, C., Rowhani, P., Ramankutty, N., 2016. Influence of extreme weather disasters on global crop production. Nature 529 (7584), 84–87.

Maclean, I.M., 2020. Predicting future climate at high spatial and temporal resolution. Glob. Chang. Biol. 26 (2), 1003–1011.

Maclean, I.M., Suggitt, A.J., Wilson, R.J., Duffy, J.P., Bennie, J.J., 2017. Fine-scale climate change: modelling spatial variation in biologically meaningful rates of warming. Glob. Chang. Biol. 23 (1), 256–268.

Maclean, I.M., Mosedale, J.R., Bennie, J.J., 2019. Microclima: an r package for modelling meso-and microclimate. Methods Ecol. Evol. 10 (2), 280–290.

Met Office, 2016. South West England: climate. Available at. https://www.metoffice.gov.uk/research/climate/maps-and-data/regional-climates/index. accessed: May 2020.

Met Office Hadley Centre, 2018. UKCP18 Regional Projections on a 12km grid over the UK for 1980–2080. Retrieved from. https://catalogue. ceda.ac.uk.

Mosedale, J.R., Abernethy, K.E., Smart, R.E., Wilson, R.J., Maclean, I.M., 2016. Climate change impacts and adaptive strategies: lessons from the grapevine. Glob. Chang. Biol. 22 (11), 3814–3828.

Narouei-Khandan, H.A., Halbert, S.E., Worner, S.P., van Bruggen, A.H., 2016. Global climate suitability of citrus huanglongbing and its vector, the Asian citrus psyllid, using two correlative species distribution modelling approaches, with emphasis on the USA. Eur. J. Plant Pathol. 144 (3), 655–670.

Parker, L.E., Abatzoglou, J.T., 2018. Shifts in the thermal niche of almond under climate change. Clim. Chang. 147 (1–2), 211–224.

Peltonen-Sainio, P., Jauhiainen, L., Laurila, H., Sorvali, J., Honkavaara, E., Wittke, S., Puttonen, E., 2019. Land use optimization tool for sustainable intensification of high-latitude agricultural systems. Land Use Policy 88, 104104.

Phalan, B., Green, R.E., Dicks, L.V., Dotta, G., Feniuk, C., Lamb, A., Balmford, A., 2016. How can higher-yield farming help to spare nature? Science 351 (6272), 450–451.

Posselt, R., Müller, R., Trentmann, J., Stockli, R., Liniger, M.A., 2014. A surface radiation climatology across two Meteosat satellite generations. Remote Sens. Environ. 142, 103–110.

Power, A.G., 2010. Ecosystem services and agriculture: tradeoffs and synergies. Philosoph. Transac. Royal Soc. B: Biol. Sci. 365 (1554), 2959–2971.

R Core Team, 2019. R: A language and environment for statistical computing. Version 3.6.0.

Ramankutty, N., Rhemtulla, J., 2012. Can intensive farming save nature? Front. Ecol. Environ. 10 (9), 455–455.

Reynolds, R.W., Smith, T.M., Liu, C., Chelton, D.B., Casey, K.S., Schlax, M.G., 2007. Daily high resolution-blended analyses for sea surface temperature. J. Clim. 20 (22), 5473–5496.

Richards, M., Pogson, M., Dondini, M., Jones, E.O., Hastings, A., Henner, D.N., Milner, S., 2017. High-resolution spatial modelling of greenhouse gas emissions from land-use change to energy crops in the United Kingdom. GCB Bioenergy 9 (3), 627–644.

Rötter, R.P., Palosuo, T., Kersebaum, K.C., Angulo, C., Bindi, M., Ewert, F., Olesen, J.E., 2012. Simulation of spring barley yield in different climatic zones of Northern and Central Europe: a comparison of nine crop models. Field Crops Research 133, 23–36.

Rudel, T.K., Schneider, L., Uriarte, M., Turner, B.L., DeFries, R., Lawrence, D., Birkenholtz, T., 2009. Agricultural intensification and changes in cultivated areas, 1970–2005. Proceedings of the National Academy of Sciences 106 (49), 20675–20680.

Sax, D.F., Early, R., Bellemare, J., 2013. Niche syndromes, species extinction risks, and management under climate change. Trends Ecol. Evol. 28 (9), 517–523.

Scherer, L.A., Verburg, P.H., Schulp, C.J., 2018. Opportunities for sustainable intensification in European agriculture. Glob. Environ. Chang. 48, 43–55.

Stocker, T.F., Qin, D., Plattner, G.K., Tignor, M., Allen, S.K., Boschung, J., Midgley, P.M., 2013. Climate change 2013: The physical science basis. Cambridge University Press, Cambridge.

Ummenhofer, C.C., Meehl, G.A., 2017. Extreme weather and climate events with ecological relevance: a review. Philosoph. Transac. Royal Soc. B: Biol. Sci. 372 (1723), 20160135.

van der Velde, M., Biavetti, I., El-Aydam, M., Niemeyer, S., Santini, F., van den Berg, M., 2019. Use and relevance of European Union crop monitoring and yield forecasts. Agric. Syst. 168, 224–230.

Watthanawisuth, N., Tuantranont, A., Kerdcharoen, T., 2009. Microclimate real-time monitoring based on ZigBee sensor network. In: SENSORS. IEEE, pp. 1814–1818.

Wunder, S., 2001. Ecuador goes bananas: Incremental technological change and forest loss. In: Angelsen, A., Kaimowitz, D. (Eds.), Agricultural Technologies and Tropical Deforestation. CABI Publishing in association with CIFOR, New York, pp. 167–194.

Yao, S., Merwin, I.A., Bird, G.W., Abawi, G.S., Thies, J.E., 2005. Orchard floor management practices that maintain vegetative or biomass groundcover stimulate soil microbial activity and alter soil microbial community composition. Plant Soil 271 (1–2), 377–389.