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National Horizon Scanning for Future Crops Under a Changing UK Climate

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ABSTRACT

Most national assessments of climate change-related risks to agriculture focus on the productivity of existing crops. However, one adaptation option is to switch to alternative crops better suited to changing local climates. Spatially explicit projections of relative climatic suitability across a wide range of crops can identify which ones might be viable alternatives. Parametrising process-based models for multiple crops is complex, so there is value in using simpler approaches to 'horizon scan' to identify high-level issues and target further research. We present a horizon scan approach based on EcoCrop data, producing mapped changes in suitability under +2°C and +4°C warming scenarios (above pre-industrial), for over 160 crops across the United Kingdom. For the United Kingdom, climate change is likely to bring opportunities to diversify cropping systems. Many current and potential new crops show widespread increases in suitability under a +2°C warming scenario. However, under a +4°C scenario, several current crops (e.g. onions, strawberries, oats, wheat) begin to show declines in suitability in the region of the United Kingdom where most arable crops are currently grown. Whilst some new crops with increasing suitability may offer viable alternatives (e.g. soy, chickpea, grapes), the greatest average increases in suitability across crops occur outside the UK's current areas of greatest agricultural production. Realising these opportunities would thus be likely to require substantial changes to current farming systems and supply chains. By highlighting these opportunities and challenges, our approach provides potentially valuable information to farmers and national assessments.

1 | Introduction

Climate change is projected to bring significant challenges to agricultural systems worldwide (Ray et al. 2019, Raza et al. 2019, Wheeler and von Braun 2013, Zabel, Putzenlechner, and Mauser 2014, Zhao et al. 2017) at a time when they must also increase productivity to meet growing global demand for food (Tilman et al. 2011). If the global food supply system is to maintain resilience in the face of climate change, it is vital for farmers to successfully adapt their agricultural systems, management, and technologies.

One key potential route of adaptation is for farmers to switch to alternative crops that are better suited to changing local climates (Rising and Devineni 2020). The majority of global agricultural systems (and of the world's food supply) rely on a relatively small subset of crop species (Hammer 2004, Hufnagel, Reckling, and Ewert 2020). In many situations, our ability to continue increasing crop yields via technological solutions has stalled (Arata, Fabrizi, and Sckokai 2020, Grassini, Eskridge, and Cassman 2013), and there is evidence that climate change has already contributed to this 'drag' on the growth of agricultural production (Bezner Kerr et al. 2022). Simultaneously, introducing more diverse cropping systems has been demonstrated to deliver a wide range of other benefits to agroecosystems including improvements to biodiversity, soil health and the control of pests and diseases (Altieri et al. 2015, Guzman, Chase, and Kremen 2019, Hufnagel, Reckling, and Ewert 2020). Adopting a more diverse range of alternative or underutilised crops, therefore, has the potential to both increase climate resilience and support farmland biodiversity and ecosystem services.

Whilst switching to alternative crops offers opportunities, it also brings potential risks that may act as barriers to adoption (Rial-Lovera, Davies, and Cannon 2017). These include economic risks of investment in new agronomic practices and technology, and access to local supply chains (Holloway and Ilbery 1997, Knight et al. 2022). There are also environmental risks of introducing crops novel to a given location, including interactions with pollinators, wild crop relatives (Haygood, Ives, and Andow 2003) and pests (Skendžić et al. 2021). If adopting alternative crops is to succeed as an adaptation strategy, it is vital that decisions are based on robust data. However, one factor known to be limiting uptake of alternative crops is a lack of accessible, spatially detailed data on climatic suitability of a large variety of different crops. This restricts our ability to make informed decisions on alternative crops as viable local adaptation strategies (Knight et al. 2022, Rial-Lovera, Davies, and Cannon 2017).

An essential first step towards overcoming this limitation is to develop spatially explicit projections for crops under climate change. Whilst there is an extensive literature modelling climatic impacts on individual crops (Agnolucci et al. 2020, Challinor et al. 2009, Jagermeyr et al. 2021, Rezaei et al. 2023, Rial-Lovera, Davies, and Cannon 2017, Wheeler and von Braun 2013, Zhao et al. 2017), application of these models to explore climate change impacts is usually limited to a small number of species (Hufnagel, Reckling, and Ewert 2020, Rezaei et al. 2023). Comparisons scoping multiple crop species, including those not yet grown in the focal area, are rarer (Aramburu Merlos and Hijmans 2022, Ciscar, Fisher-Vanden, and Lobell 2018, Heinz, Galetti, and Holzkämper 2024, Hufnagel, Reckling, and Ewert 2020, Manners, Varela-Ortega, and van Etten 2020). The justification for focussing on a few crops is, typically, that they currently occupy the majority of the global cropped area (Agnolucci et al. 2020, Jagermeyr et al. 2021, Zabel, Putzenlechner, and Mauser 2014, Zhao et al. 2017). However, this neglects the potential for this situation to change (Aramburu Merlos and Hijmans 2022, Pironon et al. 2019) and excludes crops of potentially high importance at local levels. A resolution to this issue is to conduct 'horizon scans', estimating spatial and temporal patterns of change in the suitability under climate change, for a wide range of crops, at national to sub-national resolutions. Horizon scans do not, in themselves, seek to produce predictions with high levels of absolute accuracy but instead aim to provide a high-level overview and help prioritise targets for further investigation (Boult et al. 2018) or to identify research and knowledge gaps (Manners and van Etten 2018). Horizon scanning approaches are widespread and provide valuable data for the development of adaptation strategies in the agricultural, environmental and policy sectors, while also guiding further research (Sutherland and Woodroof 2009). Some horizon scans have used review-based methods (Knight et al. 2022) or global-scale data (Fischer et al. 2021), but these are limited in their spatial and temporal resolution.

Here, we develop a high-resolution, spatially explicit model of changes in relative crop suitability under climate change, based on an existing database of crop biophysical constraints, EcoCrop (FAO 2022). Models built on EcoCrop have been widely used to assess crop potential before (e.g. Egbebiyi et al. 2020, Hijmans and Graham 2006, Manners, Varela-Ortega, and van Etten 2020, Ramirez-Villegas, Jarvis, and Läderach 2013, Taba-Morales et al. 2020) and have shown good correspondence with more complex models (Hijmans and Graham 2006, Ramirez-Villegas, Jarvis, and Läderach 2013, Vermeulen et al. 2013). Although EcoCrop focuses on major environmental constraints (i.e. climate and soil types) and does not encompass many other parameters that ultimately determine the viability of a crop in a given location, it forms an ideal method for horizon scanning, as it does not require local parametrisation and can be run rapidly for a large number of crops on fine-resolution gridded data. We used this model, combined with CHESS-SCAPE climate projections downscaled from the UKCP18 Regional Climate Model perturbed parameter ensemble (Robinson et al. 2023), to perform a horizon scan for the United Kingdom. Our results project changes in suitability for 167 arable, horticultural and orchard crops, at 1-km resolution for two levels of global average warming (+2°C and +4°C above pre-industrial). We identify changes in the suitability of both current and alternative crops and explore potential opportunities and challenges in using alternative crops to adapt the UK agricultural system to climate change.

2 | Methods

2.1 | Filtering the EcoCrop Database

The EcoCrop database (accessible at https://gaez.fao.org/pages/EcoCrop) was developed by the Food and Agricultural Organization (FAO) of the United Nations in the 1990s and gives climatic and abiotic threshold values for over 1700 crop species. The database has been widely used to explore climatic constraints on crops, and modelling approaches have been developed for calculating suitability indices from EcoCrop data. These models have subsequently been built into analytical software (Hijmans 2021, Hijmans et al. 2001) and have been used for exploring climate-driven changes in suitability for individual crops (Hunter and Crespo 2019, Ramirez-Villegas, Jarvis, and Läderach 2013, Taba-Morales et al. 2020) and for comparisons across crop species (Chemura, Gleixner, and Gornott 2024, Gardner, Gaston, and Maclean 2021, Heinz, Galetti, and Holzkämper 2024, Manners and van Etten 2018, Manners, Varela-Ortega, and van Etten 2020) over local, national, continental and global scales. Models based on EcoCrop are well suited to horizon scanning exercises as they typically require few crop-specific parameters (Ramirez-Villegas, Jarvis, and Läderach 2013), cover a large number of crops and have been demonstrated to show good correspondence to more complex models where these are applied for the same crops, regions and time periods (Hijmans and Graham 2006, Ramirez-Villegas, Jarvis, and Läderach 2013). We constructed our own model based on the EcoCrop database rather than directly implementing existing models, partly to maximise the potential of the fine spatial and temporal (daily as opposed to monthly data) resolution of the UK-specific climate data, adding maximum temperature, and partly to give us full control over the way the model handles issues like annual versus perennial crops and the compound effects of temperature and precipitation suitability. Because the model developed by Hijmans et al. (2001) is generally referred to as 'the EcoCrop model' in the literature, so we henceforth refer to 'our EcoCrop model' to distinguish our specific methods from this prior implementation.

We first filtered the EcoCrop database by several criteria. Firstly, we excluded crops for which information was missing on one or more parameters required by our model. Secondly, we excluded crops which would not be expected to occur in the United Kingdom even under extensive climate change (e.g. those associated with tropical climates or soil types that are not found in the United Kingdom). Finally, we also restricted analyses to those species which are used for food and excluded those that are used solely for timber, materials, medicines or ornamental uses. This was done primarily to focus our analyses on crops that are likely to be governed by similar market forces (e.g. those governing food supply chains) and political factors (e.g. national food security). In some cases, this distinction is somewhat unclear as the same crop can be used for multiple purposes. For example, hemp (*Cannabis sativa*) is grown variously for food, fibre and medicinal products depending on the variety and local demand. In such cases, we included a crop as long as it is grown for food in at least some situations. We also included crops that are grown for food but contribute little to overall macronutrient output (e.g. aromatics such as thyme *Thymus vulgaris* and sage *Salvia officinalis*) because they are still part of the food supply chain and may contribute to maintaining diets with sufficient micronutrients.

We also added information on whether the crop is known to be currently grown in the United Kingdom as a current UK major crop, defined as crops contributing to the cumulative 90% of agricultural land in the United Kingdom, from UK government Department for Environment, Food and Rural affairs (Defra) statistics. This category is designed to be broadly indicative of the relative importance of crops to current UK agriculture, and thus the impact of climate change on the UK's dominant cropping systems, rather than any attempt to formally group crops. We did not directly consider whether crops are grown under protected (e.g. glasshouse) or irrigated conditions, because this information is hard to obtain in a spatially explicit manner and the vast majority of the UK's crops are grown under rainfed, open-field conditions. However, even if climatic suitability can be modified by such management practices, we assume that changes in suitability are still informative as they indicate that these practices are likely to have greater or lesser changes to overcome in future. We also assigned each crop to a 'crop type':

1. **Bush and vine fruits—**annual or perennial species producing edible berries or other fruits, including shrubs, vines and herbaceous species.
2. **Cereals**—annual herbaceous species producing edible seeds, either true cereals (graminoids) or pseudocereals.
3. **Legumes**—annual herbaceous species in the family Fabaceae producing edible pulses.
4. **Oilseeds—**annual herbaceous species producing edible oils, extracted from seeds or fruits.
5. **Root crops**—mostly herbaceous species with edible below-ground roots, rhizomes, bulbs, corms or tubers.
6. **Tree fruits**—perennial shrub and tree species, producing edible fruits or nuts.
7. **Vegetables and herbs**—annual herbaceous species with edible leaves, flowers or fruits.

Crop types were derived from the lifespan, lifeform and use category classes in EcoCrop and were intended to capture broad types of crop production system (see Appendix S2). Crop types are defined such that individual farms in the United Kingdom are likely to specialise in a few types, with adaptation to new systems requiring greater investment in terms of new machinery and agronomic knowledge and skills.

2.2 | Source of Climate Projections

We used gridded climate data from CHESS-SCAPE (Robinson et al. 2022, Robinson et al. 2023). These are 1-km resolution projections of meteorological variables over the United Kingdom at daily time steps, from 1980 to 2080. These data provide UK climate change data that have high temporal and spatial resolution, are consistent with historical observations and demonstrate a range of possible climate change scenarios. CHESS-SCAPE provides several physical climate variables over the United Kingdom for the period 1980–2080 at 1-km spatial resolution and time steps ranging from daily to decadal averages. We used the downscaled RCP8.5 data from CHESS-SCAPE and ran models with the four ensemble members in the dataset. These ensemble members were derived from the UKCP18 12 km Regional Climate Model perturbed parameter ensemble and selected from the 12 UKCP18 ensemble members to span the range of temperature and precipitation change in the UKCP18 ensemble, representing the ensemble climate model uncertainty (Robinson et al. 2022, 2023) (see Figures S2 and S3).

Because we were interested in exploring changes in suitability at alternative levels of global warming, it was necessary to select the appropriate time slices from the ensemble members, that is those corresponding to +2°C and +4°C of global warming relative to the pre-industrial period (1850–1900). This was done using existing time slices for the UKCP18 12 km ensemble (Arnell et al. 2021). These time slices were derived from the global temperature time series associated with the global model simulation in which each of the regional climate model simulations is nested (Kennedy-Asser et al. 2022). For all four ensemble members, at least 90% of the time slice within which +4°C of global average warming occurred falls before 2080. It is worth noting that, in the baseline period (1980–2000, against which climatic suitability under each warming level is compared), global warming of approximately +0.5°C had already occurred relative to 1850–1900; hence, the changes in suitability projected exclude any changes that had already occurred by then.

Since the results presented here focus on projected changes in an index of suitability with +2°C and +4°C of global warming rather than a measure of absolute suitability over time, it was considered unnecessary to bias correct the UKCP18 output. Preliminary analysis suggested that the direction, magnitude and spatial patterns of change in suitability indices were consistent whether bias correction was applied or not.

2.3 | Linking EcoCrop and Climate Projections

We constructed a model to derive gridded estimates of climate-based crop suitability indices from the information in the EcoCrop database (henceforth referred to as 'our model'). The model derives a climatic suitability score based on daily temperature and daily precipitation values, using information on the required and optimal temperature and precipitation ranges, and the number of days within which the crop must grow (parameter names are as used in the EcoCrop database):

- *GMIN, GMAX*: the minimum and maximum time required to produce a harvestable crop in days
- *TMIN, TMAX*: the minimum and maximum temperatures for crop growth in degree Celsius
- *TOPMN, TOPMX*: the optimal temperature range for crop growth in degree Celsius
- *PMIN, PMAX*: the minimum and maximum of precipitation for crop growth in millimetre
- *POPMN, POPMX*: the optimal precipitation range for crop growth in millimetre
- *KTMP*: temperature below which the crop plant dies in degree Celsius
- *TEXT*: soil texture classes suitable for the crop (e.g. heavy, medium, light, organic)

Values for these parameters as derived from the EcoCrop database are given in Appendix S2. The temperature and precipitation suitability score for a given crop is calculated for each day (i.e. each hypothetical sowing date for annual crops, or hypothetical start of the annual cycle for perennial crops) and grid square in the CHESS-SCAPE dataset and a selection of possible growing times (*GTIME* s) between *GMIN* and *GMAX* by looking forward in time by *GTIME* days and calculating the scores for this period. We chose *GTIME*s at an interval of 10 days from *GMIN* onwards to balance accuracy against computational cost. The main steps in the model are as follows:

1. S_T is calculated via annual or perennial scoring method.
2. Heat and frost penalties are applied to S_T.
3. Steps 1 and 2 are repeated for each *GTIME*.
4. S_P is calculated.
5. S_T and S_P are aggregated over *GTIME* by taking the maximum.
6. Scores are aggregated from daily to annual by taking the 95th percentile.
7. Minimum of aggregated S_T and S_P is calculated, producing combined climatic suitability score.
8. Soil-type and land-cover masking is applied.
9. Combined suitability score is converted from annual to degree Celsius of warming.
10. Difference from 1980 to 2000 baseline is calculated.

The temperature score S_T is calculated by two different methods dependent on whether or not the crop is usually grown as an annual or perennial crop. This is due to a fundamental difference in the way the EcoCrop parameters are interpreted for these different life histories—annual plants must complete their entire growth cycle from sowing to harvest within *GTIME* days, whilst perennials are only required to complete production of their harvestable parts (e.g. fruit) within *GTIME* days. Preliminary analyses suggested that applying the annual method to perennials gave many species very low suitability scores (including those currently grown in the United Kingdom), whilst using the perennial methods for annuals resulted in very high scores, even for species that are not currently grown in the European Union. We took life-history information (and thus the method used to model each crop) directly from the EcoCrop database. The derivation of the combined climatic suitability score via the model follows the equations below. Full model code is available via the URL in the Data Availability Statement, and pseudocode is provided in Appendix S1.

2.4 | Annual Temperature Suitability Scoring Method

For annual crops, $S_{T,d,g,gt}$ is calculated using the following method:

For each day (d), 1-km grid cell (g) and *GTIME* length (gt), an intermediate score between 0 and 1 is assigned using Equations (1) to (4):

$$D_{d,g,gt} = \frac{T_{d,g} - TMIN}{TOPMN - TMIN} \text{ when } TMIN < T_{d,g} \leq TOPMN, \tag{1}$$

$$D_{d,g,gt} = 1 \text{ when } TOPMN < T_{d,g} \leq TOPMX, \tag{2}$$

$$D_{d,g,gt} = \frac{TMAX - T_{d,g}}{TMAX - TOPMX} \text{ when } TOPMX < T_{d,g} \leq TMAX, \tag{3}$$

$$D_{d,g,gt} = 0 \text{ for all other } Td, g, \tag{4}$$

where $T_{d,g}$ is the average temperature of the given day (d) and grid cell (g). A score of 1 represents a day and grid cell that is maximally temperature suitable for the given crop, and 0 not suitable. Then, a sum of $D_{d,g,gt}$ across the subsequent *GTIME* days is calculated according to Equation (5):

$$N_{d,g,gt} = \sum_{\text{day}=d}^{\text{day}=d+GTIME} D_{d,g,gt}. \tag{5}$$

This sum, $N_{d,g,gt}$, is the total number of suitable days within *GTIME*. If $N_{d,g,gt}$ is greater than or equal to *GMIN*, thar is, if at least the minimum number of suitable days is achieved within *GTIME*, then a suitability score, S_T, dependent only on the given *GTIME*, is assigned to the given day (d), grid cell (g) and *GTIME* (gt) according to Equation (6):

$$S_{T,d,g,gt} = 100 \times \left[1 - \frac{GTIME - GMIN}{GMAX - GMIN}\right], \quad \text{where } N_{d,g,gt} \geq GMIN, \text{ else } S_{T,d,g,gt} = 0. \tag{6}$$

The result of Equations (1) to (6) is that the fewer days it takes to amass *GMIN* suitable days, the higher the temperature suitability score ($S_{T,d,g,gt}$). If every day within a window size of *GMIN* is maximally suitable (Equation 2), $S_{T,d,g,gt}$ is 100 (as $N_{d,g,gt} = GMIN$ and $GTIME = GMIN$ in Equation 6). If the window size has to increase to *GMAX* before $N_{d,g,gt}$ equals or exceeds *GMIN*, then $S_{T,d,g,gt} = 0$ (as $N_{d,g,gt} \geq GMIN$ and $GTIME = GMAX$ in Equation 6). This represents the assumption that, all other considerations aside, the shorter the feasible development time within which a crop reaches its climatically constrained conditions for growth, the greater its suitability to the local climate.

Heat stress and frost penalties are then applied to the suitability score to account for temperature extremes. Daily minimum temperatures within the *GTIME* window are checked, and if there is a daily-minimum temperature below *KTMP*, then $S_{T,d,g,gt}$ is set to 0. A heat stress penalty is also applied by subtracting the number of days within the *GTIME* window with a daily maximum temperature above *TMAX* from $S_{T,d,g,gt}$. It is the highest score out of all the window sizes (*GTIME*s) assessed that is taken forward (Step 5):

$$S_{T,d,g} = \max_{gt \in [GMIN,\ GMAX]} S_{T,d,g,gt}, \tag{7}$$

so a climate where the majority of days are temperature suitable for a given crop (assessed by Equations 1–4) will score higher than a climate with more variable temperature suitability.

2.5 | Perennial Temperature Suitability Scoring Method

The temperature score for a given *GTIME* (gt), each day (d), grid square (g) and crop is calculated as follows:

First, the daily average temperature (*TAVG*) across *GTIME* is calculated. Then, Equations (8) to (10) are used to calculate the score, $S_{T,d,g,gt}$:

$$S_{T,d,g,gt} = \frac{100}{0.5\,(TOPMX + TOPMN) - TMIN}\left(TAVG_{d,g,gt} - TMIN\right) \tag{8}$$

when $TMIN < TAVG_{d,g,gt} \leq 0.5(TOPMX + TOPMN)$,

$$S_{T,d,g,gt} = \frac{100}{TMAX - 0.5\,(TOPMX + TOPMN)}\left(TMAX - TAVG_{d,g,gt}\right) \tag{9}$$

when $TMAX \geq TAVG_{d,g,gt} > 0.5(TOPMX + TOPMN)$,

$$S_{T,d,g,gt} = 0 \text{ for all other TAVG}d, g, gt. \tag{10}$$

2.6 | Precipitation Suitability Scoring Method

The precipitation score is calculated in a similar way. The precipitation total ($PTOT_{d,g,gt}$) is calculated over the *GTIME* period:

$$PTOT_{d,g,gt} = \sum_{\text{day}=d}^{\text{day}=d+GTIME} P_{d,g,gt}. \tag{11}$$

Then, Equations (12) to (14) are used:

$$S_{P,d,g,gt} = \frac{100}{0.5\,(POPMX + POPMN) - PMIN}\left(PTOT_{d,g,gt} - PMIN\right) \tag{12}$$

when $PMIN < PTOT_{d,g,gt} \leq 0.5(POPMX + POPMN)$,

$$S_{P,d,g,gt} = \frac{100}{PMAX - 0.5\,(POPMX + POPMN)}\left(PMAX - PTOT_{d,g,gt}\right) \tag{13}$$

when $PMAX \geq PTOT_{d,g,gt} > 0.5(POPMX + POPMN)$,

$$S_{P,d,g,gt} = 0 \text{ for all other } PTOTd, g, gt. \tag{14}$$

As for the temperature suitability score, it is the highest score out of all the window sizes (*GTIME*s) assessed that is taken forward (Step 5):

$$S_{P,d,g} = \max_{gt \in [GMIN,\ GMAX]} S_{P,d,g,gt}. \tag{15}$$

2.7 | Handling Output Suitability Scores

The scores $S_{P,d,g,gt}$ and $S_{T,d,g,gt}$ are then aggregated over *GTIME* (gt) and time (d). They are first aggregated by taking the maximum score across *GTIME*s (e.g. Equation 7), then the scores for each hypothetical sowing day (d) are aggregated to yearly scores by taking the 95th percentile over each year. Using the 95th percentile ensures that the aggregated annual score represents the best possible score derived from the optimal timing of crop growth and harvest, without being overly sensitive to anomalous single days with high scores (as would be the case if the maximum was used). The independent calculation for temperature and precipitation suitability allows us to examine the relative contribution of changes in temperature and precipitation, but a final, unitless combined climatic suitability score for a given grid square was also derived from the minimum of the two scores at each grid square (g), as the lowest score is likely to be the limiting factor in the crop's growth.

Although our analysis focusses on climatic factors, we also wished to ensure that the suitability sores reflected other major abiotic restrictions on the feasibility of potential future crops—namely soils and landscape structure. Soil masking was applied to the combined temperature and precipitation suitability scores according to the *TEXT* parameter, using British Geological Survey Soil Parent Material Model mapped data. Masking for agricultural land was also applied for all crops using the UKCEH 1 km Land-Cover Map 2015 (Rowland et al. 2017). In the UK situation, the likelihood of growing crops on land which is currently not used for crops of any sort (including pastures) is likely to be unfeasible, given that over 70% of the UK's land is already farmed (Rowland et al. 2017) and there is strong competition with other land uses for the remainder (Smith et al. 2023). We applied masking at the end of our processing chain, so that our methods could be applied in situations where information about these constraints was either lacking or unnecessary.

Our model thus produces as its final output a 1-km grid for each crop, mapping a unitless climatic suitability score ranging between 0 and 100. A value of zero indicates the required climatic parameters are never met within even the minimum growing period required by the crop, whilst a value of 100 indicates that all climatic parameters are met throughout the growing period whenever the crop is planted. We chose to present a continuous score rather than a binary score of suitable versus unsuitable, as this better reflects the potential uncertainties associated with our approach and interpretation is less strongly sensitive to how accurately the values in the EcoCrop database represent the climatic constraints on a crop and all its varieties, cultivars and production systems.

Because the model produces annual outputs, data can be analysed either in terms of change over time or with reference to particular levels of warming. We chose the latter approach because it renders the output more agnostic to the particular RCP used to produce the climate projections and because we focus solely on the climatic impacts whilst not accounting for other factors with a known temporal component (e.g. land-use change, CO_2 concentration). To do this, we identified the range of years for each ensemble member within which the average global temperature increases by the required amount, with reference to the baseline condition (1980–2000), as described above and detailed in Arnell et al. (2021). We then averaged the output combined climatic suitability score across the time periods to obtain our suitability indices for +2°C and +4°C warming levels and then took the mean across the four ensemble members. Variability in the ensemble members can be seen in Figures S2 and S3.

2.8 | Summarising Changes Across Crops

We then explored change in suitability scores between the baseline, +2°C and +4°C scenarios for each crop. We summarised median change across the entire United Kingdom and per region (regions defined by aggregated EU Nomenclature of Territorial Units for Statistics Level 1). Regions were aggregated as follows: northwest = Northern Ireland, North West England; northeast = Scotland, Yorkshire and the Humber, North East England; southeast = East Midlands, London, South East England, Eastern England; southwest = Wales, West Midlands, South West England. To map aggregate change in suitability across crops, for each 1-km cell, we calculated the median difference between the suitability score under a given time slice and the baseline, across all crops. All spatial analyses were performed in R (R Core Team 2022), making use of the terra (Hijmans et al. 2022) and ncdf4 (Pierce 2019) packages.

2.9 | Model Validation

A full validation of our model is challenging, as no empirical data exist for future time periods. Even for the baseline period, comparing our modelled outputs to observed measures of crop production in the United Kingdom is challenging, as data on crop yields at sub-national scales are not published by the UK government beyond a few cereal and oilseed crops. Using data on crop areas, which can be obtained from earth observation data (e.g. Upcott et al. 2023), has the issue that current cropping patterns in the United Kingdom do not well represent climatic suitability but instead the constraints of land-use history, supply chains, yield focus, and agricultural infrastructure. An alternative approach that avoids this issue is to compare our modelled outputs to those using process-based models of crop yield. We performed this qualitatively during model development to ensure that our results showed similar temporal and spatial patterns to those of published results from statistical or process-based models applied to crops in the United Kingdom (e.g. Harrison and Butterfield 1996; Hayman et al. 2024; Holloway and Ilbery 1997; Kenny and Harrison 1992). We also performed a post hoc quantitative comparison of our outputs for the baseline period against the Global Gridded Crop Model Intercomparison (GGCMI) dataset of the Agricultural Model Intercomparison and Improvement Project (AgMIP), one of the few published datasets derived from a consistent run of the same crop models at fine (subnational) resolution, for a reasonable diversity of crops. We took data on 11 crops from the WOFOST model runs of the AgMIP GGCMI dataset with direct equivalence to those in EcoCrop and compared our suitability score against the modelled yield as a ratio of median global yield (to standardise all crops onto the same score despite their differing expected yields). We performed this comparison for the centroids of all 0.5-arc-degree cells in the AgMIP GGCMI data that overlapped our EcoCrop-derived maps (to compare the models' prediction of per-crop spatial patterns within the United Kingdom), as well as comparing the UK median value across crops (to compare the models' prediction of relative suitability across crops). Correlations between values from the two models were assessed using Pearson's r.

3 | Results

3.1 | Exploring the Fate of Current UK Crops Under Climate Change

By translating annual values to time slices corresponding to levels of average global warming (Arnell et al. 2021), we compared changes in suitability scores under +2°C and +4°C warming scenarios as well as spatial patterns within these scenarios (maps for example crops in Figure S1). Most crops showed spatial variation in suitability, both under the baseline period (1980–2000) and under warming scenarios, reflecting climatic differences within the United Kingdom (Figure S2). We summarised the crop suitability scores for the baseline and warming levels by regions, formed from aggregated EU Nomenclature of Territorial Units for Statistics Level 1. This captures spatial variation in suitability (and change thereof) and differentiates crops showing uniform versus contrasting spatial patterns.

Under a +2°C scenario, most of the UK's current major crops (defined as crops contributing to the cumulative 90% of agricultural land in the United Kingdom, from Defra statistics) show slight to substantial increases in suitability (Table 1). These increases are most marked for the northeast and northwest and

TABLE 1 | Median change per region in modelled suitability scores for 13 UK major crops, for +2°C and +4°C warming scenarios.

+2°C					+4°C				
Crop	**SW**	**NW**	**NE**	**SE**	**Crop**	**SW**	**NW**	**NE**	**SE**
Maize	14.65	43.35	51.84	9.55	Maize	17.77	50.52	62.03	8.23
Broad bean	24.39	49.00	44.42	9.90	Broad bean	23.71	61.35	59.10	6.35
Oats	8.45	19.23	26.35	4.06	Oats	1.16	24.48	34.23	−1.94
Potato	12.08	23.32	21.61	4.68	Potato	12.29	30.61	31.42	9.48
Sugarbeet	6.71	9.03	13.52	3.94	Pear	21.00	18.87	19.16	20.48
Wheat	0.19	6.39	10.90	1.19	Apple	5.32	18.55	12.71	−0.35
Pear	9.29	8.19	8.48	9.23	Sugarbeet	8.65	15.65	15.68	10.90
Apple	5.10	9.10	7.23	1.23	Raspberry	7.81	12.13	3.94	5.55
Barley	1.29	3.84	6.39	1.71	Wheat	−5.90	5.45	11.00	0.39
Raspberry	4.00	6.06	2.97	2.19	Peas	8.39	7.29	2.97	5.19
Onion	−0.23	0.61	3.97	1.06	Barley	1.03	4.39	7.84	3.55
Peas	3.65	3.10	1.90	1.77	Onion	−1.90	0.55	3.65	1.84
Strawberry	−1.15	−0.29	3.00	1.31	Strawberry	−7.23	−4.84	−0.40	0.19

Note: Rows are ordered in descending order of maximum regional change per scenario. Cells shaded on a diverging colour ramp, with grey indicating values near zero, reds indicating negative values and greens indicating positive values.

for crops like maize (*Zea mays*) and broad beans (*Vicia faba*) which are grown extensively in considerably hotter and drier climates than of the United Kingdom. Only onions (*Allium cepa*) and strawberries (*Fragaria chilensis*/*Fragaria virginiana*) show regional decreases at +2°C, and these are potentially offset by increases elsewhere. Even under +4°C of warming, no current major crops show uniform decreases in suitability across all UK regions (although strawberries come close, showing declines in three of the four regions). However, the north–south contrast becomes more marked, and regional decreases or plateaus in suitability (i.e. little to no change) are apparent for more crops, including major cereals wheat (*Triticum aestivum*) and oats (*Avena sativa*).

3.2 | Horizon Scanning for Alternative Crop Opportunities

When identifying potential alternative crops for the future, it is important to consider both the absolute score and the level of change. For example, a crop showing a moderate increase to a high suitability (say, an increase from 70 to 80) is likely to be a more viable option (and a lower risk of adoption to farmers) than one showing a larger increase from lower suitability (from 0 to 20). We therefore filtered our results for the 154 crops not classified as the UK's major crops by both the absolute score and the level of change in suitability (Table 2).

Many crops showed substantial increases under climate change that achieved high absolute scores. Amongst the greatest increases under climate change, especially under the +2°C scenario (Table 2), were those shown by crops that are currently only grown within a limited area of the United Kingdom (e.g. chickpea [*Cicer arietinum*], sunflower [*Helianthus annuus*], grape [*Vitis vinifera*]). Whilst limited areas at present may be due to several reasons, including restricted demand or access to supply chains, limitations can also reflect where climate is currently only suitable across part of the United Kingdom, and thus, a northward expansion under climate change is highly likely. A few such crops do not appear in Table 2 (e.g. quinoa [*Chenopodium quinoa*], lentils [*Lens culinaris*]), because their baseline suitability is already sufficiently high that regional increases do not place them in the top 30 (Appendix S2). Substantial increases in suitability were also evident in many crops that are currently not grown commercially in the United Kingdom, especially under the +4°C scenario. These include crops currently grown in Mediterranean Europe (e.g. *Citrus* species, durum wheat [*Triticum durum*], okra [*Abelmoschus esculentus*]) and others more associated with arid (e.g. cow pea [*Vigna unguiculata*]) or subtropical (e.g. buffalo bean [*Mucuna pruriens*]) climates in other parts of the world.

The most straightforward route for adoption of new crops is likely to be where they can be added to or substitute for crops in the current rotation of a particular agricultural system, such that the same agricultural methods, equipment and knowledge can be used (e.g. the replacement of common wheat with durum wheat). Adaptation is likely to be considerably harder where crop types are different (e.g. annuals to perennials, cereals to root crops). Figure 1 shows that the crops showing greatest increases under both warming scenarios include many arable crops (legumes, cereals and oilseeds) but also several fruit crops (e.g. *Citrus* spp., pomegranate [*Punica granatum*]) which may be viable additions or substitutions to current orchard systems (Figure 1).

3.3 | Mapping Regional Opportunities and Challenges

Mapping the median change across all crops (Figure 2) shows that both global warming scenarios result in a net increase in

TABLE 2 | Median change per region in modelled suitability scores for potential future crops, for +2°C and +4°C global warming scenarios.

+2°C					+4°C				
Crop	SW	NW	NE	SE	Crop	SW	NW	NE	SE
Sorghum	42.48	9.40	3.45	46.97	Sorghum	74.45	65.55	59.81	71.13
Andean lupin	29.97	3.97	0.29	35.68	Safflower	64.71	60.00	49.65	51.45
Safflower	35.39	12.61	3.61	35.03	Durum wheat	52.00	63.06	44.71	37.77
Wild strawberry	21.45	34.29	27.74	14.29	Okra	42.19	63.00	39.32	19.00
Durum wheat	34.16	19.52	11.03	24.58	Andean lupin	62.55	57.24	36.23	59.06
Oca	21.90	32.32	18.10	10.94	Cow pea	61.52	42.03	27.55	41.32
Horseradish	28.00	30.98	16.39	18.03	Horseradish	22.45	53.84	42.55	9.77
Okra	29.97	30.94	18.81	14.39	Oca	21.84	51.35	39.29	11.26
Sesame	14.13	25.87	22.19	4.23	Wild strawberry	13.10	48.87	43.39	6.84
Chickpea	7.13	18.81	17.81	3.29	Soy bean	35.58	44.23	17.61	10.84
Algerian oat	10.77	16.10	18.52	6.16	Shallot	43.65	36.61	12.84	16.94
Basil	4.48	17.87	16.71	2.29	Tepary bean	26.94	40.16	21.26	8.77
Hop	16.19	16.19	16.87	13.68	Buffalo bean	39.87	34.81	18.39	23.65
Caper	15.71	15.29	15.29	12.71	Sesame	20.84	38.23	32.74	9.58
Black mulberry	15.26	14.45	15.10	12.13	Cherimoya	33.19	34.65	25.06	15.32
Beetroot	6.29	14.52	4.74	−1.52	Caper	30.23	34.42	34.39	22.26
Dill	4.27	14.37	11.65	1.61	Hop	25.23	34.42	34.06	20.06
Parsnip	2.55	11.35	14.26	2.77	Black mulberry	31.32	33.48	32.94	19.48
American pawpaw	12.19	14.13	10.87	3.77	Sweet weed	31.65	33.10	24.87	14.77
Hemp	5.48	12.77	13.74	2.81	Mexican avocado	22.55	31.65	26.68	14.52
Bur-reed	10.39	13.61	9.29	6.19	Algerian oat	16.42	26.55	29.29	9.13
Linseed	6.16	12.45	13.39	3.26	Feijoa	26.52	28.61	28.74	19.29
Feijoa	13.19	12.81	12.81	11.06	American pawpaw	17.32	28.65	20.48	7.16
Tef	7.00	12.81	11.06	2.45	Bur-reed	14.19	27.71	15.55	8.52
Salsify	−8.35	5.03	12.06	−3.48	Grape	26.03	24.60	25.32	22.71
Sunflower	4.74	9.35	12.03	3.00	Chickpea	13.45	25.90	21.94	8.16
Grape	11.61	10.94	11.58	10.71	Quince	23.81	25.06	20.00	14.45
Rye	2.81	8.23	11.55	1.26	Crab apple	20.32	24.03	21.42	6.74
Crab apple	9.55	11.45	11.45	5.39	Bitter orange	23.81	22.52	22.42	19.77
Amaranth	1.32	5.65	11.35	0.84	Mandarin	22.29	21.87	22.81	14.97

Note: Rows are ordered in descending order of maximum regional change per scenario. Crops shown are the top 30 of those achieving a score of at least 40 in at least one region and showing an increase of at least 10 in at least one region. These thresholds are arbitrary, and the full list of regional median scores and changes can be found in Appendix S2. Cells shaded on a diverging colour ramp, with grey indicating values near zero, reds indicating negative values and greens indicating positive values.

suitability across most of the United Kingdom in comparison with the 1980–2000 baseline. Decreases in suitability are largely equalled (+2°C) or outweighed (+4°C) by increases. This is explained by the far larger number of potential future crops showing increases in suitability than current crops showing decreases.

Figure 2 shows that the areas with the greatest overall increase in median suitability (i.e. the greatest number of crops showing at least this level of increase) lie mostly in southwest England, Wales and Scotland, whilst the southeast of England shows the lowest median change (particularly under +4°C). This suggests that there are potentially fewer options for alternative crops in the latter region, with those crops which increase in suitability in these areas doing so to a lesser extent than in the north and west of the United Kingdom.

3.4 | Validation Results

Comparing our suitability scores with the yield predictions from the WOFOST AgMIP GGCMI data for individual crops (Table 3)

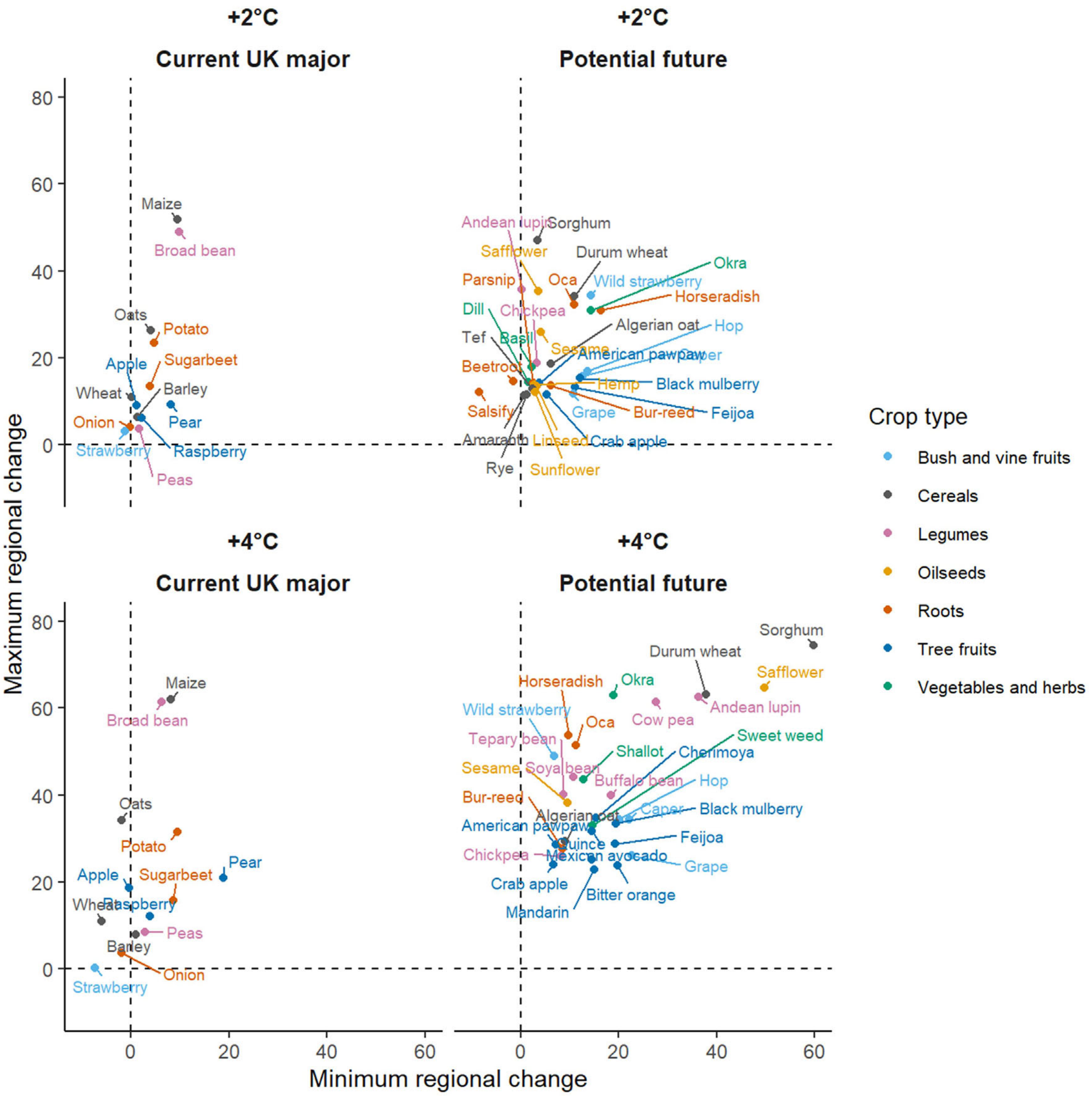

FIGURE 1 | Scatterplot of regional variation (minimum regional median change vs. maximum regional median change) in ensemble mean suitability score change from the baseline (1980–2000) under +2°C or +4°C global warming scenarios for all crops shown in Tables 1 and 2. Points and labels are coloured by their associated broad crop type.

showed correlation coefficients between 0.07 (barley) and 0.83 (maize). For crops that are currently unsuited to the UK climate, or show only very limited suitability (e.g. groundnut, rice, soy), one or both datasets predicted zero scores across most of the United Kingdom, so a meaningful correlation was not possible to calculate.

Sunflowers showed a non-significant correlation but also had the lowest viable sample size of points with data as, in this case, the AgMIP GGCMI data show a sharp cutoff to zero values outside the south east of England. Barley also showed a non-significant correlation, but this may be because of its relatively uniform suitability across the United Kingdom in both datasets (i.e. lowest range of values in Table 3).

For UK median scores, there was a strong positive relationship ($r = 0.82$, $p = 0.02$, $n = 11$) between the two models, with crops that score highly under our EcoCrop model being predicted to have high yields by AgMIP GGCMI (Figure 3).

4 | Discussion

4.1 | Climate Change Opportunities and Challenges for UK Agriculture

Our horizon scan shows the potential impacts of climate change on the UK's suitability for a wide range of crops. At first glance, climate change would appear to bring many opportunities to UK agriculture. We find that none of the UK's current major crops showed UK-wide declines in suitability, under either warming scenario. There are also substantial increases in suitability for many crops not currently grown widely in the United Kingdom, which might be feasible to incorporate into existing agricultural

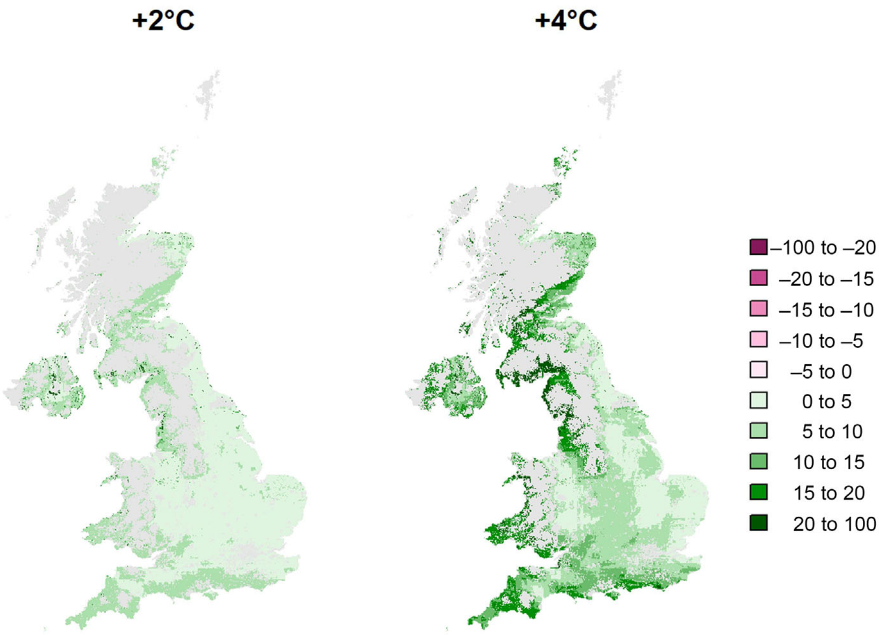

FIGURE 2 | Median change in suitability across all crops relative to the 1980–2000 baseline, under +2°C and +4°C warming scenarios. Areas shaded in grey represent 1-km cells with no agricultural land.

TABLE 3 | Correlations between EcoCrop suitability scores and AgMIP GGCMI yields for a grid of 0.5-arc-degree cell centroids across the United Kingdom.

	Correlations			Range	
Crop	***r***	***p***	***N***	**EcoCrop suitability**	**AgMIP GGCMI yield**
Barley	0.07	0.67	37	66.39–92.39	3.07–6.6
Common bean	0.34	0.04	37	34.35–92.16	0.74–4.03
Groundnut	—	—	—	—	—
Maize	0.83	<0.01	43	10.45–87.45	0.86–7.6
Potato	0.41	0.02	34	35.48–77.55	4.58–15.3
Rice	—	—	—	—	—
Rye	0.22	0.15	43	55.74–90.45	1.02–8.16
Soy	—	—	—	—	—
Sunflower	0.12	0.55	27	37.1–80.26	1.97–2.62
Wheat	0.37	0.02	37	54.1–91.84	4.37–10.08
Sorghum	—	—	—	—	—

Note: Correlations calculated via Pearson's *r*. Sample sizes vary as some crops returned no data in the AgMIP GGCMI data; dashes indicate where nonzero values were insufficient for correlation. Also showed are the ranges of the values used to calculate these correlations (note these are not the full ranges of the entire dataset).

systems. This brings opportunities to diversify UK cropping systems to increase climate resilience and bring other environmental benefits, as increasing crop heterogeneity favours biodiversity and associated ecosystem service delivery (Altieri et al. 2015; Hufnagel, Reckling, and Ewert 2020; Vernooy 2022). Crops that showed increased suitability under climate change came from a broad range of crop types, including many legumes (e.g. chickpea, cow pea, soy, broad bean). Legumes are important as protein sources allowing dietary shifts away from livestock (Kim et al. 2020; Semba et al. 2021) and reducing reliance on fertilisers through nitrogen fixation (Palmero et al. 2022). Therefore, again, adopting these crops could bring co-benefits alongside climate resilience.

However, many crops showed strong spatial variation in suitability change, with some regions experiencing increased suitability while others exhibited declines. These included some of the UK's major crops, with wheat, oats, apples, onions and strawberries all showing regional declines under the +4°C scenario. Spatial variation is to be expected, given the baseline of strong latitudinal and longitudinal gradients in precipitation and temperature across the United Kingdom, and that change in precipitation and (to

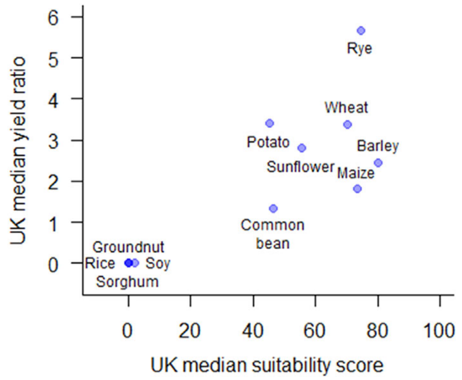

FIGURE 3 | Comparison of UK median scores from EcoCrop against UK median yields as a ratio of the global median from AgMIP GGCMI.

a lesser extent) temperature is also spatially variable (Robinson et al. 2023) (Figure S2). The challenges of climate change to current crops are exacerbated by the fact that, where crops did show regional declines, these were often in southeast England, which currently contains the most extensive and productive arable land and most diverse range of crop types (Upcott et al. 2023). Whilst production of major crops might simply shift to match changing suitability (Sloat et al. 2020), there are limits to this method of adaptation. The areas of the United Kingdom showing greatest increases in average suitability across crops (e.g. the southwest and Scottish borders) are constrained by factors including small field sizes, variable topography and isolation from much of the current infrastructure of crop processing and supply chains, which limit the extent to which production of major crops is likely to shift to these areas (Millward and Robinson 1971). More localised supply chains (Berti 2020; Maye and Ilbery 2006) and the drive to reduce greenhouse gas emissions from the food processing sector by reducing transport miles and increasing the number of local processors supported by on-site renewable energy production (Clairand et al. 2020) may help bypass some of these constraints but will not escape them altogether.

Switching crops within current highly agricultural areas also faces challenges. Whilst cereal crops that showed declines in the southeast (e.g. common wheat, oats) often showed alternatives with increasing suitability in the same region (e.g. durum wheat, Algerian oats [*Avena byzantina*]), the average change in suitability is lowest in this region, suggesting that overall options are more limited. Indeed, there were fewer alternatives for soft fruits and vegetables, which are important micronutrient sources (Keatinge et al. 2010). There are therefore likely to be considerable challenges in adapting UK agricultural systems to realise the potential opportunities that climate change provides for alternative crops and crop diversification. Overcoming these challenges is likely to require careful balancing of the relative benefits of crop switching versus other routes towards increased climate resilience. These may include changing crop varieties or breeding of greater resilience into existing crops (Pironon et al. 2019) or the adoption of novel agricultural systems (such as paludiculture or vertical farming) that may be more resilient to climate change but require fundamental changes to the way land is used and managed (Rhymes et al. 2023). Indeed, region-specific pathways of climate change adaptation for crops must be framed within the wider challenge of adapting land use as a whole. A potential use of our suitability maps is thus as a parameter in spatially explicit modelling of competing land uses (e.g. forestry, urban development) to explore scenarios that can resolve conflicts by ensuring that land-use change is allocated to the most suitable location under climate change and minimising environmental and socioeconomic trade-off (e.g. Smith et al. 2023).

4.2 | Limitations of the Horizon Scanning Approach

Our suitability scores assume that crops are grown under rainfed, open-field conditions. This is reflected in the low baseline scores for a few crops that are currently grown in the United Kingdom but do not form a substantial percentage of the cropped area (e.g. lettuce [*Lactuca sativa*], pumpkin [*Cucurbita maxima*]), because climatic conditions are in fact modified by a variety of agricultural practices for some or all of the crop life cycle (e.g. irrigation, protection, transplanting), all of which are management methods that our model does not directly consider (although more detailed exploration of the balance between which of the temperature and precipitation suitable scores is the more limiting may provide some indication of viability of management as a route toward adaptation). Whilst these practices allow viable production in otherwise 'unsuitable' climates, they are only worthwhile where incentives outweigh costs. Our results indicate the climatic 'envelope' within which such actions can modify conditions. Thus, crops that show declines in suitability but which are grown under modified conditions (e.g. strawberries, over 80% of which are grown under cover in the United Kingdom [Calleja, Ilbery, and Mills 2012]) may still become more challenging to produce, because the climatic constraints that must be overcome by management are larger. This is exacerbated by the potential for climate change to increase the costs of agricultural practices, both economically (e.g. rising costs of agricultural energy and materials [Zilberman et al. 2008]) and environmentally (e.g. the need to reduce energy consumption and implement nature-based solutions [Keesstra et al. 2018; Seddon et al. 2020]).

Many factors beyond climatic suitability also limit the viability and uptake of alternative crops. Information is also required on the associated agronomy, pest and disease risks and predicted economic returns (Knight et al. 2022), as well as on the influence of climate and weather on these. A potential issue is the fraction of the potential alternative crops which may be insect pollinated, in the context of projections of large global declines in insect pollinators (Warren et al. 2018) above 2°C warming. This could act as a major constraint on the feasibility of switching to these crops.

Equally, it is important that environmental impacts of new crops are adequately explored. Whilst our results focus on broad climatic constraints alone, these form the background against which other factors interact to shape current and future cropping decisions. Our approach, in common with others based on the EcoCrop database (Gardner, Gaston, and Maclean 2021; Heinz, Galetti, and Holzkämper 2024), cannot model the effects of CO_2 fertilisation, the complexities of soil water storage or the impact of short-lived weather events (e.g. convection driven summer storms) that are less well-simulated by the climate projections (Robinson et al. 2023), but which may ultimately be more restrictive on crop viability than long-term average climatic shifts. However, by using daily as opposed to monthly data, we are able to better estimate the potential impacts of those extremes of temperature and precipitation that are captured by the input climate projections. Our results, as with any horizon scan (Gardner, Gaston, and Maclean 2021), are thus intended to help prioritise candidates for further investigation into these issues, for example by construction, parametrisation and application of more detailed, process-based models of crop yield. Early indications of where to focus such efforts are potentially valuable. For example, crops identified as becoming more suitable may require adaptation (by traditional plant breeding or by new genetic technologies) to ensure that they can be grown at scale in the United Kingdom (Eshed and Lippman 2019; Rial-Lovera, Davies, and Cannon 2017; Tadele 2019). Since plant breeding programmes are expensive and long term, our results can help to identify current crops requiring breeding programmes to counter falling suitability or new candidate crops requiring breeding to increase agronomic viability (Pironon et al. 2019).

Our modelling approach is simple in comparison to the statistical or process-based approaches frequently used to assess single crop responses to climate change (Ciscar, Fisher-Vanden, and Lobell 2018; Rosenzweig et al. 2014). Where statistical or process-based models have been applied to potential future crops for the United Kingdom, our approach does tend to produce similar spatial patterns of predicted change in suitability. These include the initial rise under moderate warming for wheat, followed by a strong north–south split under increased warming (Harrison and Butterfield 1996; Hayman et al. 2024), as well as the widespread increases seen for grapes, sunflower and common bean. Although the corelation of our score to yield produced by AgMIP GGCMI varied between crops in terms of spatial pattens within the United Kingdom, all correlation coefficients were positive, and the correlation between UK medians across crops was significant. This suggests that even where our approach does not reproduce the exact spatial patterns of modelled crop yield, it is likely to be suitable for the relative ranking of crops over larger spatial units, as we present here. Where other studies have used the existing EcoCrop model as developed by Hijmans et al. (2001) or Hijmans (2021), the crops identified as showing the greatest increases in suitability in the United Kingdom are broadly similar to the shortlists we present, including lupin, flax, sunflower and hemp (Gardner, Gaston, and Maclean 2021), as well as broad bean, lentil, chickpeas, cow pea and soy bean (Manners, Varela-Ortega, and van Etten 2020).

More complex models also have limitations for horizon scanning. Statistical approaches require empirical observations on crop parameters and climatic drivers at relevant spatial resolutions, which are often unavailable for crops not currently grown within the area of interest. Process-based models require development and local parameterisation for each crop of interest, which is challenging across large numbers of crops. Results are often varied depending on which model is used (Asseng et al. 2013; Jagermeyr et al. 2021) and the assumptions made when parametrising complex processes such as CO_2 fertilisation (Rezaei et al. 2023). Our approach allows us to use a single model to scope relative climate change impacts across a wide range of crops without historic observations, in line with the growing use of such approaches (Aramburu Merlos and Hijmans 2022; Chemura, Gleixner, and Gornott 2024; Heinz, Galetti, and Holzkämper 2024; Manners, Varela-Ortega, and van Etten 2020; Pironon et al. 2019). Our horizon scan can then be used to prioritise crops for more detailed investigation via more complex models or experimentation, which can explore areas that our modelling approach does not address. Even without further modelling, our 1-km gridded outputs can be overlain with other datasets to identify spatial conflicts and trade-offs with other ecosystem services or climate risks (e.g. Arnell et al. 2021).

4.3 | Benefits of National Scale Horizon Scanning Approaches

Climate change impacts on agricultural production are already being felt (Ray et al. 2019; Sloat et al. 2020). Adaptation strategies are being developed across agricultural systems, ranging from the actions of individual farmers to the design of national policies. In the United Kingdom, farmers are relatively able and willing to adopt new crops, with 33%–39% of arable farmers planning to increase the range of crops they grow in the immediate future (Defra 2019). Indeed, several of the alternative crops showing increased suitability under both warming levels have had their first commercial UK harvests in recent years (e.g. soy, chickpeas, common bean [*Phaseolus vulgaris*]). Others are not yet grown in the United Kingdom but are grown elsewhere. Such 'orphan', 'neglected' or 'underutilised' crops (Knight et al. 2022; Tadele 2019) have already been identified as important potential sources of climate-resilient alternatives. However, if adopting new crops is to succeed as an adaptation strategy, it is vital that it is based on robust data at scales relevant to the agricultural sector. Although assessments of climate impacts on crops are often presented at global scale (Agnolucci et al. 2020; Aramburu Merlos and Hijmans 2022; Jagermeyr et al. 2021; Ray et al. 2019; Rosenzweig et al. 2014; Zabel, Putzenlechner, and Mauser 2014; Zhao et al. 2017), and the United Kingdom is not a 'breadbasket' in terms of the global crop supply, there are several reasons why horizon scanning exercises are worth performing at the national/sub-national scales presented here.

Firstly, these are the scales at which much agricultural policy is formulated, and within which agricultural systems are likely to be governed by similar market forces, land-use histories, environmental constraints and agronomic practices. Secondly, crops which are staples in an individual country may be excluded from global analyses if they form a small part of the global agricultural system (Pironon et al. 2019; Tadele 2019). Thirdly, reliance on global breadbaskets is increasingly precarious under climate change (Gaupp et al. 2019; Gaupp et al. 2020), so it is important for individual nations to be able to plan their agricultural futures to increase their resilience, and trends within individual countries may contrast completely with those at global scales. For example, our result of increasing suitability for maize in the United Kingdom runs counter to predictions for decreased maize yields under climate change in the regions that currently produce most of the global supply (Jagermeyr et al. 2021; Rezaei et al. 2023). Finally, as demonstrated by our results, countries are not uniform spatial entities and can show considerable spatial variation in the trajectories and impacts of climate change. As competition for land becomes more intense under climate change (Harvey and Pilgrim 2011; Lamb et al. 2016), spatial data enabling agriculture to target the most productive crops and areas become increasingly valuable. Indeed, one of the factors currently limiting uptake of new crops is the lack of accessible information on climatic suitability of crops for particular areas (Knight et al. 2022; Rial-Lovera, Davies, and Cannon 2017). Understanding spatial variation in climate change impacts at within-nation scales is thus key to successful adaptation of agricultural systems. Without data on which to base plans for adaptation by alternative crops, agricultural systems are likely to be 'locked in' to current crops (Oliver et al. 2018), with adaptations failing to keep pace with climate change (Sloat et al. 2020) or relying on practices which exacerbate climate-driven issues, for example irrigation increasing water scarcity (Grafton et al. 2018).

In conclusion, we have demonstrated a rapid and flexible way of horizon scanning climatic suitability for multiple crops for the United Kingdom, which is readily transferable to other countries and situations. Our results illustrate the value of this approach as a potentially valuable addition to national assessments, both for shortlisting individual crops for further investigation and for providing a systems-level overview of the opportunities and challenges in adapting national crop systems for climate resilience.

Author Contributions

John Redhead: investigation, visualisation, writing–original draft. **Matt Brown**: investigation, methodology, software, data curation, visualisation. **Jeff Price**: conceptualisation, methodology. **Emma Robinson**: resources, methodology. **Robert Nicholls**: supervision, project administration. **Rachel Warren**: methodology. **Richard Pywell**: conceptualisation, supervision. All authors contributed to the review and editing of the draft manuscript.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are openly available from a variety of repositories. CHESS-SCAPE data are available from the CEDA Archive, https://doi.org/10.5285/8194b416cbee482b89e0dfbe17c5786c (Robinson et al. 2022).

EcoCrop parameters and the output suitability data are available from the Data & Analytics Facility for National Infrastructure (DAFNI): https://facility.secure.dafni.rl.ac.uk/data/details?dataset_id=a6c74c27-d37b-441b-887a-aded8daf407e&version_id=3e97b4d2-63bf-4427-af98-72ac8489aa3f&metadata_id=3e8ef184-17bf-4516-a570-bd1e8a8813f9.

Model code is available from GitHub: https://github.com/OpenCLIM/EcoCrop

References

Agnolucci, P., C. Rapti, P. Alexander, et al. 2020. "Impacts of Rising Temperatures and Farm Management Practices on Global Yields of 18 Crops." *Nature Food* 1: 562–571.

Altieri, M. A., C. I. Nicholls, A. Henao, and M. A. Lana. 2015. "Agroecology and the Design of Climate Change-Resilient Farming Systems." *Agronomy for Sustainable Development* 35: 869–890.

Aramburu Merlos, F., and R. J. Hijmans. 2022. "Potential, Attainable, and Current Levels of Global Crop Diversity." *Environmental Research Letters* 17: 044071.

Arata, L., E. Fabrizi, and P. Sckokai. 2020. "A Worldwide Analysis of Trend in Crop Yields and Yield Variability: Evidence From FAO Data." *Economic Modelling* 90: 190–208.

Arnell, N. W., A. Freeman, A. L. Kay, A. C. Rudd, and J. A. Lowe. 2021. "Indicators of Climate Risk in the UK at Different Levels of Warming." *Environmental Research Communications* 3: 095005.

Asseng, S., F. Ewert, C. Rosenzweig, et al. 2013. "Uncertainty in Simulating Wheat Yields Under Climate Change." *Nature Climate Change* 3: 827–832.

Berti, G. 2020. "Sustainable Agri-Food Economies: Re-Territorialising Farming Practices, Markets, Supply Chains, and Policies." *Agriculture* 10: 64.

Bezner Kerr, R., T. Hasegawa, R. Lasco, et al. 2022. "Food, Fibre, and Other Ecosystem products." In *Climate Change 2022: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, edited by H.-O. Pörtner, D. C. Roberts, M. Tignor, et al. 713–906. Cambridge, UK: Cambridge University Press.

Boult, M., V. Jassal, R. S. de Souza, et al. 2018. *Horizon Scanning: A Practitioner's Guide*. London: IRM - Institute of Risk Management.

Calleja, E. J., B. Ilbery, and P. R. Mills. 2012. "Agricultural Change and the Rise of the British Strawberry Industry, 1920–2009." *Journal of Rural Studies* 28: 603–611.

Challinor, A. J., F. Ewert, S. Arnold, E. Simelton, and E. Fraser. 2009. "Crops and Climate Change: Progress, Trends, and Challenges in Simulating Impacts and Informing Adaptation." *Journal of Experimental Botany* 60: 2775–2789.

Chemura, A., S. Gleixner, and C. Gornott. 2024. "Dataset of the Suitability of Major Food Crops in Africa Under Climate Change." *Scientific Data* 11: 294.

Ciscar, J.-C., K. Fisher-Vanden, and D. B. Lobell. 2018. "Synthesis and Review: An Inter-Method Comparison of Climate Change Impacts on Agriculture." *Environmental Research Letters* 13: 070401.

Clairand, J. M., M. Briceño-León, G. Escrivá-Escrivá, and A. M. Pantaleo. 2020. "Review of Energy Efficiency Technologies in the Food Industry: Trends, Barriers, and Opportunities." *IEEE Access* 8: 48015–48029.

Department for Environment Food and Rural Affairs (Defra). 2019. *Farm Practices Survey Autumn 2019*. London: Defra.

Egbebiyi, T. S., O. Crespo, C. Lennard, et al. 2020. "Investigating the Potential Impact of 1.5, 2 and 3°C Global Warming Levels on Crop Suitability and Planting Season Over West Africa." *PeerJ* 8: e8851.

Eshed, Y., and Z. B. Lippman. 2019. "Revolutions in Agriculture Chart a Course for Targeted Breeding of Old and New Crops." *Science* 366: eaax0025.

Fischer, G., F. O. Nachtergaele, H. T. van Velthuizen, et al. 2021. Global Agro-Ecological Zones v4 – Model Documentation. Rome, Italy: FAO.

Food and Agriculture Organization (FAO). 2022. *ECOCROP: Database of Crop Constraints and Characteristics*. Rome, Italy: FAO.

Gardner, A. S., K. J. Gaston, and I. M. D. Maclean. 2021. "Combining Qualitative and Quantitative Methodology to Assess Prospects for Novel Crops in a Warming Climate." *Agricultural Systems* 190: 103083.

Gaupp, F., J. Hall, S. Hochrainer-Stigler, and S. Dadson. 2020. "Changing Risks of Simultaneous Global Breadbasket Failure." *Nature Climate Change* 10: 54–57.

Gaupp, F., J. Hall, D. Mitchell, and S. Dadson. 2019. "Increasing Risks of Multiple Breadbasket Failure Under 1.5 and 2 °C Global Warming." *Agricultural Systems* 175: 34–45.

Grafton, R. Q., J. Williams, C. J. Perry, et al. 2018. "The Paradox of Irrigation Efficiency." *Science* 361: 748–750.

Grassini, P., K. M. Eskridge, and K. G. Cassman. 2013. "Distinguishing Between Yield Advances and Yield Plateaus in Historical Crop Production Trends." *Nature Communications* 4: 2918.

Guzman, A., M. Chase, and C. Kremen. 2019. "On-Farm Diversification in an Agriculturally-Dominated Landscape Positively Influences Specialist Pollinators." *Frontiers in Sustainable Food Systems* 3: 87.

Hammer, K. 2004. *Resolving the Challenge Posed by Agrobiodiversity and Plant Genetic Resources: An Attempt*. Kassel, Germany: Kassel University Press.

Harrison, P. A., and R. E. Butterfield. 1996. "Effects of Climate Change on Europe-Wide Winter Wheat and Sunflower Productivity." *Climate Research* 07: 225–241.

Harvey, M., and S. Pilgrim. 2011. "The New Competition for Land: Food, Energy, and Climate Change." *Food Policy* 36: S40–S51.

Haygood, R., A. R. Ives, and D. A. Andow. 2003. "Consequences of Recurrent Gene Flow From Crops to Wild Relatives." *Proceedings of the Royal Society of London. Series B: Biological Sciences* 270: 1879–1886.

Hayman, G., J. W. Redhead, M. Brown, et al. 2024. "A Framework for Improved Predictions of the Climate Impacts on Potential Yields of UK Winter Wheat and Its Applicability to Other UK Crops." *Climate Services* 34: 100479.

Heinz, M., V. Galetti, and A. Holzkämper. 2024. "How to Find Alternative Crops for Climate-Resilient Regional Food Production." *Agricultural Systems* 213: 103793.

Hijmans, R. J. 2021. Recocrop: Estimating Environmental Suitability for Plants. R package version 0.4-0.

Hijmans, R. J., R. Bivand, K. Forner, J. Ooms, E. Pebesma, and M. D. Sumner. 2022. terra: Spatial Data Analysis. R package.

Hijmans, R. J., and C. H. Graham. 2006. "The Ability of Climate Envelope Models to Predict the Effect of Climate Change on Species Distributions." *Global Change Biology* 12: 2272–2281.

Hijmans, R. J., L. Guarino, M. Cruz, and E. Rojas. 2001. "Computer Tools for Spatial Analysis of Plant Genetic Resources Data: 1. DIVA-GIS." *Plant Genetic Resources Newsletter* 127: 15–19.

Holloway, L. E., and B. W. Ilbery. 1997. "Global Warming and Navy Beans: Decision Making by Farmers and Food Companies in the U.K." *Journal of Rural Studies* 13: 343–355.

Hufnagel, J., M. Reckling, and F. Ewert. 2020. "Diverse Approaches to Crop Diversification in Agricultural Research. A Review." *Agronomy for Sustainable Development* 40: 14.

Hunter, R., and O. Crespo. 2019. "Large Scale Crop Suitability Assessment Under Future Climate Using the EcoCrop Model: The Case of Six Provinces in Angola's Planalto Region." In *The Climate-Smart Agriculture Papers: Investigating the Business of a Productive, Resilient and Low Emission Future*, edited by T. S. Rosenstock, A. Nowak, and E. Girvetz, 39–48. Cham, Switzerland: Springer International Publishing.

Jagermeyr, J., C. Muller, A. C. Ruane, et al. 2021. "Climate Impacts on Global Agriculture Emerge Earlier in New Generation of Climate and Crop Models." *Nature Food* 2: 873–885.

Keatinge, J. D. H., F. Waliyar, R. H. Jamnadas, et al. 2010. "Relearning Old Lessons for the Future of Food—By Bread Alone No Longer: Diversifying Diets With Fruit and Vegetables." *Crop Science* 50: S-51–S-62.

Keesstra, S., J. Nunes, A. Novara, et al. 2018. "The Superior Effect of Nature Based Solutions in Land Management for Enhancing Ecosystem Services." *Science of The Total Environment* 610–611: 997–1009.

Kennedy-Asser, A. T., G. Owen, G. J. Griffith, et al. 2022. "Projected Risks Associated With Heat Stress in the UK Climate Projections (UKCP18)." *Environmental Research Letters* 17: 034024.

Kenny, G. J., and P. A. Harrison. 1992. "The Effects of Climate Variability and Change on Grape Suitability in Europe." *Journal of Wine Research* 3: 163–183.

Kim, B. F., R. E. Santo, A. P. Scatterday, et al. 2020. "Country-Specific Dietary Shifts to Mitigate Climate and Water Crises." *Global Environmental Change* 62: 101926.

Knight, S., L. Smith, P. Howell, et al. 2022. *Review of Opportunities for Diversifying UK Agriculture Through Investment in Underutilised Crops*. Defra Project CH0224. Cambridge, UK: NIAB.

Lamb, A., R. Green, I. Bateman, et al. 2016. "The Potential for Land Sparing to Offset Greenhouse Gas Emissions From Agriculture." *Nature Climate Change* 6: 488–492.

Manners, R., and J. van Etten. 2018. "Are Agricultural Researchers Working on the Right Crops to Enable Food and Nutrition Security Under Future Climates?" *Global Environmental Change* 53: 182–194.

Manners, R., C. Varela-Ortega, and J. van Etten. 2020. "Protein-Rich Legume and Pseudo-Cereal Crop Suitability Under Present and Future European Climates." *European Journal of Agronomy* 113: 125974.

Maye, D., and B. Ilbery. 2006. "Regional Economies of Local Food Production: Tracing Food Chain Links between 'Specialist' Producers and Intermediaries in the Scottish–English Borders." *European Urban and Regional Studies* 13: 337–354.

Millward, R., and A. H. W. Robinson. 1971. *The South-West Peninsula*. London: MacMillan and Co.

Oliver, T. H., E. Boyd, K. Balcombe, et al. 2018. "Overcoming Undesirable Resilience in the Global Food System." *Global Sustainability* 1: e9.

Palmero, F., J. A. Fernandez, F. O. Garcia, et al. 2022. "A Quantitative Review Into the Contributions of Biological Nitrogen Fixation to Agricultural Systems by Grain Legumes." *European Journal of Agronomy* 136: 126514.

Pierce, D. 2019. *'ncdf4': Interface to Unidata netCDF (Version 4 or Earlier) Format Data Files*. R package.

Pironon, S., T. R. Etherington, J. S. Borrell, et al. 2019. "Potential Adaptive Strategies for 29 Sub-Saharan Crops Under Future Climate Change." *Nature Climate Change* 9: 758–763.

R Core Team 2022. *R: A Language and Environment for Statistical Computing* (R Version 3.6.3 - 4.2.1). Vienna, Austria: R Foundation for Statistical Computing.

Ramirez-Villegas, J., A. Jarvis, and P. Läderach. 2013. "Empirical Approaches for Assessing Impacts of Climate Change on Agriculture: The EcoCrop Model and a Case Study With Grain Sorghum." *Agricultural and Forest Meteorology* 170: 67–78.

Ray, D. K., P. C. West, M. Clark, J. S. Gerber, A. V. Prishchepov, and S. Chatterjee. 2019. "Climate Change Has Likely Already Affected Global Food Production." *PLoS ONE* 14: e0217148.

Raza, A., A. Razzaq, S. S. Mehmood, et al. 2019. "Impact of Climate Change on Crops Adaptation and Strategies to Tackle Its Outcome: A Review." *Plants* 8: 34.

Rezaei, E. E., H. Webber, S. Asseng, et al. 2023. "Climate Change Impacts on Crop Yields." *Nature Reviews Earth & Environment* 4: 831–846.

Rhymes, J., E. Stockdale, B. Napier, et al. 2023. The Future of UK Vegetable Production. Technical report. https://www.wwf.org.uk/our-reports/future-uk-vegetable-production-technical-report.

Rial-Lovera, K., W. P. Davies, and N. D. Cannon. 2017. "Implications of Climate Change Predictions for UK Cropping and Prospects for Possible Mitigation: A Review of Challenges and Potential Responses." *Journal of the Science of Food and Agriculture* 97: 17–32.

Rising, J., and N. Devineni. 2020. "Crop Switching Reduces Agricultural Losses From Climate Change in the United States by Half Under RCP 8.5." *Nature Communications* 11: 4991.

Robinson, E. L., C. Huntingford, V. S. Semeena, and J. M. Bullock. 2022. *CHESS-SCAPE: Future Projections of Meteorological Variables at 1 Km Resolution for the United Kingdom 1980–2080 Derived From UK Climate Projections 2018*. Didcot, UK: NERC EDS Centre for Environmental Data Analysis.

Robinson, E. L., C. Huntingford, V. S. Semeena, and J. M. Bullock. 2023. "CHESS-SCAPE: High Resolution Future Projections of Multiple Climate Scenarios for the United Kingdom Derived From Downscaled UKCP18 Regional Climate Model Output." *Earth System Science Data* 15, no. 12: 5371–5401.

Rosenzweig, C., J. Elliott, D. Deryng, et al. 2014. "Assessing Agricultural Risks of Climate Change in the 21st Century in a Global Gridded Crop Model Intercomparison." *Proceedings of the National Academy of Sciences of the United States of America* 111: 3268–3273.

Rowland, C. S., R. D. Morton, L. Carrasco, G. McShane, A. W. Neil, and C. M. Wood. 2017. *Land Cover Map 2015 (1 km Dominant Aggregate Class, GB)*. Atlanta, GA: NERC Environmental Information Data Centre.

Seddon, N., A. Chausson, P. Berry, C. A. Girardin, A. Smith, and B. Turner. 2020. "Understanding the Value and Limits of Nature-Based Solutions to Climate Change and Other Global Challenges." *Philosophical Transactions of the Royal Society B: Biological Sciences* 375: 20190120.

Semba, R. D., R. Ramsing, N. Rahman, K. Kraemer, and M. W. Bloem. 2021. "Legumes as a Sustainable Source of Protein in human Diets." *Global Food Security* 28: 100520.

Skendžić, S., M. Zovko, I. P. Živković, V. Lešić, and D. Lemić. 2021. "The Impact of Climate Change on Agricultural Insect Pests." *Insects* 12: 440.

Sloat, L. L., S. J. Davis, J. S. Gerber, et al. 2020. "Climate Adaptation by Crop Migration." *Nature Communications* 11: 1243.

Smith, A. C., P. A. Harrison, N. J. Leach, et al. 2023. "Sustainable Pathways Towards Climate and Biodiversity Goals in the UK: The Importance of Managing Land-Use Synergies and Trade-Offs." *Sustainability Science* 18: 521–538.

Sutherland, W. J., and H. J. Woodroof. 2009. "The Need for Environmental Horizon Scanning." *Trends in Ecology & Evolution* 24: 523–527.

Taba-Morales, G., G. Hyman, J. R. Mejía, et al. 2020. "Improving African Bean Productivity in a Changing Global Environment." *Mitigation and Adaptation Strategies for Global Change* 25: 1013–1029.

Tadele, Z. 2019. "Orphan Crops: Their Importance and the Urgency of Improvement." *Planta* 250: 677–694.

Tilman, D., C. Balzer, J. Hill, and B. L. Befort. 2011. "Global Food Demand and the Sustainable Intensification of Agriculture." *Proceedings of the National Academy of Sciences of the United States of America* 108: 20260–20264.

Upcott, E. V., P. A. Henrys, J. W. Redhead, S. G. Jarvis, and R. F. Pywell. 2023. "A New Approach to Characterising and Predicting Crop Rotations Using National-Scale Annual Crop Maps." *Science of The Total Environment* 860: 160471.

Vermeulen, S. J., A. J. Challinor, P. K. Thornton, et al. 2013. "Addressing Uncertainty in Adaptation Planning for Agriculture." *Proceedings of the National Academy of Sciences of the United States of America* 110: 8357–8362.

Vernooy, R. 2022. "Does Crop Diversification Lead to Climate-related Resilience? Improving the Theory Through Insights on Practice." *Agroecology and Sustainable Food Systems* 46: 877–901.

Warren, R., J. Price, E. Graham, N. Forstenhaeusler, and J. VanDerWal. 2018. "The Projected Effect on Insects, Vertebrates, and Plants of Limiting Global Warming to 1.5°C Rather Than 2°C." *Science* 360: 791–795.

Wheeler, T., and J. von Braun. 2013. "Climate Change Impacts on Global Food Security." *Science* 341: 508–513.

Zabel, F., B. Putzenlechner, and W. Mauser. 2014. "Global Agricultural Land Resources—A High Resolution Suitability Evaluation and Its Perspectives Until 2100 Under Climate Change Conditions." *PLoS ONE* 9: e107522.

Zhao, C., B. Liu, S. Piao, et al. 2017. "Temperature Increase Reduces Global Yields of Major Crops in Four Independent Estimates." *Proceedings of the National Academy of Sciences of the United States of America* 114: 9326–9331.

Zilberman, D., T. Sproul, D. Rajagopal, S. Sexton, and P. Hellegers. 2008. "Rising Energy Prices and the Economics of Water in Agriculture." *Water Policy* 10: 11–21.

Supporting Information

Additional supporting information can be found online in the Supporting Information section.