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Protein-rich legume and pseudo-cereal crop suitability under present and future European climates

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ABSTRACT

Replacing animal proteins with plant proteins in diets has been demonstrated to have both health and environmental advantages, driving a debate about the potential of protein-rich crops as dietary replacements for animal products. However, there is a lack of knowledge on how climate change could influence the potential for producing protein-rich crops. This study addresses this knowledge gap for the European Union. We analysed 13 protein-rich crops, using the crop suitability model EcoCrop and climate projections for the 2050s, based on 30 Global Circulation Models, under the Representative Concentration Pathway 4.5. The results suggest that current protein-rich crop distributions reflect climatic suitability. We demonstrate the heterogeneous impacts of climate change on crop suitability. In general, conditions in northern Europe were modelled to become more favourable for protein-rich crops, while in southern Europe modelled future climates limit the production of traditional protein-rich crops commonly grown there, including chickpea and lentil. Model results show an expanded area of high suitability for quinoa. Our results confirm the need for concerted breeding and research planning strategies to improve the tolerance of faba bean, lentil, and chickpea to the abiotic stresses that are predicted to become more common with climate change. At the same time, production in northern Europe can benefit from experimentation with protein-rich crops predicted to become more suitable there. Production planning and agricultural policy should consider these likely impacts, to encourage shifts that follow the emerging geographic patterns of crop suitability, and to support the resilience of protein-rich crop production in regions that may be negatively impacted by climate change.

1. Introduction

Several analyses have found that global increases in animal production and consumption are unsustainable (Tilman and Clark, 2014; Hallström et al., 2015; Willett et al., 2019). These findings have led many researchers to indicate the need for long-term dietary shifts and specifically the replacement of animal products by plant-based products (e.g.van Dooren et al., 2014; Berners-Lee et al., 2012; Willett et al., 2019). Harwatt et al. (2017) demonstrate the potential for replacement of animal proteins with plant proteins in developed countries. These replacements would offer benefits for human health (Bouvard et al., 2015; Becerra-Tomás et al., 2017), the environment (Cassidy et al., 2013; Springmann et al., 2016), and global food security (West et al., 2014; Erb et al., 2016). Most likely replacement products derive from protein-rich crops, including legumes and pseudo-cereals (e.g. Erb et al., 2016; Harwatt et al., 2017). Paradoxically, these crops have experienced several decades of decline in both production and consumption (Manners, 2018). This decline has been registered in several world regions, including Europe, and is due to a range of causes, both agronomic and socio-economic (Voisin et al., 2014; Zander et al., 2016). However, analyses of data up to the year 2013 indicate nascent reversals in legume production in some European countries (Manners, 2018). There are indications that the production of protein-rich crops will increase in the future, such as recent growth in demand, increasing consumer awareness of the health benefits of dietary transitions, and the projected long-term high prices of plant proteins (Pilorge and Muel, 2016; Watson et al., 2017; Clément et al., 2018).

Any increase in the production of protein-rich crops would have to address the challenge of a changing climate. Global average temperature is estimated to increase by 1.5 °C by 2100 (IPCC, 2014). This will

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have profound effects on crop productivity (Delgado et al., 2011). Changes in productivity will also lead to changes in crop distributions (Chaves et al., 2003). Therefore, decision-makers need information about possible future crop productivity patterns and geographical distributions to make strategic investments in infrastructure and capacities to grow, process, and market protein-rich crops. Crop suitability models can help to assess the impacts of climate change and generate information useful to policy makers, crop breeders, industry, and other decision-makers (Zabel et al., 2014; Jarvis et al., 2012; Hyman et al., 2013; Beebe et al., 2011). To date, large-scale analyses of climate change impacts have largely concentrated on major crops (maize, wheat, soybean, and rice) (e.g. Rosenzweig et al., 2014; Challinor et al., 2014). Protein-rich crops have received less attention. The aim of this study is to provide a foundation for pro-active planning of European production of protein-rich crops in the face of climate change.

This investigation has three specific objectives: first, to investigate the role of climate suitability in explaining contemporary protein-rich crop distributions across the EU; second, to analyse the potential impacts of future climates on the suitability of protein crops on arable land within the EU; thirdly, to identify suitable protein-rich crop options for future investigation and potential cultivation across the EU.

2. Material and methods

2.1. Crops and area

Our analysis uses current climate data (1970–2000) and future climate scenarios (2050s) across EU-28 countries to examine the current and future climate suitability for 13 protein-rich legume and pseudo-cereal crops (Table 1). These crops were selected due to their historic presence in European agriculture, their importance as human food and animal feed, and their presence in ongoing agronomic field tests (Clément et al., 2018). Crop suitability was analysed at national level (NUTS-1) and subnational level (NUTS-2) for all EU-28 Member States. NUTS (*Nomenclature of Territorial Units for Statistics)* are a standardised definition of census area. Malta was excluded due to its small agricultural area. The analysis was performed only in areas currently recognised as cropland (Ramankutty et al. 2008). Future changes in cropland area are expected due to climate change (Porfirio et al., 2017) and other non-climatic drivers (Smith et al., 2010). For simplicity, cropland area in 2050 is assumed to be the same as in 2000.

2.2. EcoCrop and extension

For the major cereal grain crops, well-developed crop growth models are available, but similar models are not available for most protein-rich crops. Therefore, we used the EcoCrop model, which is a simple, generic model. Specifically, we used the "ecocrop" function from R package *dismo* to assess the suitability of an environment for cultivation of a specified crop (Hijmans et al., 2017). As EcoCrop requires few crop-specific parameters, it can be applied to a wide range of crops, including those where less detailed ecophysiological information is available. It has been used in several studies (e.g. Ramirez-Villegas et al., 2013; Piikki et al., 2017). Vermeulen et al. (2013) demonstrated that its outputs are largely consistent with those of more complex models. Therefore, we consider EcoCrop to be an appropriate tool for developing a coarse understanding of the impacts of climate change on protein-rich crop suitability in Europe by 2050.

EcoCrop uses geospatial monthly precipitation and temperature data to assess suitability (FAO, 2016). For each crop, the model retrieves from the EcoCrop database the parameters that correspond to its acceptable temperature range, its acceptable range of total rainfall, and the length of the crop cycle. EcoCrop does not know (or assume) the best planting date for a given crop in a given place. Instead, the model simulates different possible growing seasons and selects the most suitable. Each simulated season starts on the first day of the month, one for each of the 12 months of the year. Each simulated season has the same length, determined by the corresponding crop-specific parameter in the EcoCrop database. Then, for each of the 12 simulated seasons, the model assesses whether the total rainfall and monthly temperature conditions during this period fall within the acceptable temperature and rainfall range. This produces 12 suitability values, one for each possible planting date. From this series, EcoCrop takes the highest value as crop suitability. This assumes that a farmer would plant during the most ideal season. This means that a single crop can be suitable in one area during the winter and in another area during the summer. This selection of the ideal growing season ignores the possibility of multiple crop cycles during a single year. In the comparisons between current and future climate, this approach accounts for potential shifts in planting dates as an adaptation measure taken by farmers. Suitability values range from 0 (unsuitable) to 1 (suitable). The EcoCrop model was run using current climate data to develop a contemporary baseline and were also run using climate data for the 30 Global Circulation Models (GCM) selected, under Representative Concentration Pathway (RCP) 4.5. A more detailed description of the model can be found in Manners and van Etten (2018) and Online Resource 1.

EcoCrop also permits the inclusion of additional, non-climatic, data, which potentially improve predictions (Piikki et al., 2017). However, also for these non-climatic factors, numerical niche ranges need to be defined (optimal range and absolute limits). A number of soil parameters were considered for inclusion in an "extended" (climate and soil) EcoCrop model: soil texture, soil organic matter, and soil pH. The EcoCrop database uses categories for both soil texture (light, medium, heavy) and soil organic matter (low, moderate, high), without defining the categories numerically (FAO, 2016). This precluded the inclusion of these parameters in our modelling exercises. Also, soil organic matter is not stable over time, but impacted by land use, which is difficult to predict towards 2050 (Cambardella, 2005).

For soil pH, the EcoCrop database provides numerical niche ranges (FAO, 2016), allowing us to include this parameter in our "extended" EcoCrop model. Soil pH influences the potential for crop growth through its influence on water uptake and nutrient availability (Kemmitt et al., 2006; Ghimire et al., 2017). Legumes are especially sensitive to soil pH, as it affects rhizobia establishment, plant growth, and protein and amino acid levels (Rohyadi et al., 2004; Mohammadi et al., 2012; Bekere et al., 2013; Ferreira et al., 2016). No future soil pH projections are available; we treated soil pH as static over time. The parent material is the main driving factor behind large-scale patterns in soil pH of natural soils, rather than atmospheric deposition or climate (Augusto et al., 2017). In areas where the soil pH level is outside the acceptable range, farmers can take corrective measures, such as soil amendments or increasing soil organic matter, but will incur (opportunity) costs by doing so. This cost is reflected in a lower suitability index in our extended version of the EcoCrop model.

Crop suitability, under the extended model, for each cropland pixel

Table 1
List of 13 legume and pseudo-cereals analysed.

Common Name	Scientific Name	Crop Type
Amaranth	*Amaranthus ssp.*	Pseudo-cereal
Andean lupin	*Lupinus mutabilis* Sweet	Legume
Blue lupin	*Lupinus angustifolius* L.	Legume
Buckwheat	*Fagopyrum esculentum* Moench	Pseudo-cereal
Chickpea	*Cicer arietinum* L.	Legume
Common bean	*Phaseolus vulgaris* L.	Legume
Cow pea	*Vigna unguiculata ssp. unguiculate* (L.) Walp.	Legume
Faba bean	*Vicia faba* L.	Legume
Lentil	*Lens culinaris* Medik.	Legume
Pea	*Pisum sativum* L.	Legume
Quinoa	*Chenopodium quinoa* Willd.	Pseudo-cereal
Soybean	*Glycine max* (L.) Merr.	Legume
White lupin	*Lupinus albus* L.	Legume

was defined as being the minimum value from the climatic and soil suitability values. A full explanation of the extended model can be found in Online Resource 1.

2.3. Crop, climate, and soil data

Crop suitability was modelled using climate data for present and future conditions and soil pH data. We assumed that crop breeding and varietal change will not result in a change in crop-specific climate adaptation parameters. This is important for the interpretation of our results. Some negative effects of climate change may be addressed by breeding investments.

Current climate data were sourced from WorldClim 2, which contains monthly (minimum, maximum, and mean) temperature and precipitation values. These monthly values are average levels over the period 1970–2000 (Fick and Hijmans, 2017). From WorldClim 2, we used 12 monthly layers of precipitation, minimum and mean temperature data at a resolution of 2.5 arc minutes ($\sim$4.5km^2 at the equator). Future climate data (2050s) were taken from the Climate Change, Agriculture and Food Security (CCAFS) database (Ramirez and Jarvis, 2008). These data had been previously downscaled, as described by Ramirez and Jarvis (2010). Twelve monthly data sets were collected for precipitation, minimum, and mean temperatures at a resolution of 2.5 arc minutes. Data were collected for the 30 available GCMs (Online Resource 2) under RCP4.5. RCP4.5 was selected as we consider the scenario behind this pathway (IPCC, 2014) as the most probable and informative for 2050.

We used soil pH data sourced from the International Soil Reference and Information Centre (ISRIC) and their SoilGrids platform (Hengl et al., 2017). Data represent pH at soil depths of 0, 5, 15, and 30 cm at 30 arc seconds. We averaged pH values of the entire soil profile (0 − 30 cm) using the raster package (Hijmans et al., 2016) in the R environment (R Core Team, 2016). We then aggregated the data to 2.5 arc minutes.

All data were cropped to an area from 30 °N to 75 °N and from 15 °W to 55 °E, covering all EU-28 countries.

2.4. Comparison of modelled suitability with current crop distributions

An important question is whether environmental suitability of protein-rich crops indeed constrains their current geographic distributions. We would only expect that future crop distributions are influenced by climate change if there is evidence for environmental constraints at present. To test this, we compared the environmental suitability determined by EcoCrop with agricultural production statistics for each NUTS-2 region (European Commission, 2017). Agro-ecological suitability is only one of many limiting factors, so we expect an asymmetric relationship between production and suitability. Crops can be absent in highly suitable areas, but we do not expect them to be present in highly unsuitable areas. To analyse this type of relationship we used quantile regression focusing on the highest quantile (0.95) of production.

We analysed the 5 crops for which sub-national statistical data were available. We used production area data for the year 2010 for blue lupin, buckwheat, faba bean, pea, and soybean. The proportional distribution of each crop, in all NUTS-2 regions, was calculated from the total production of all protein-rich crops within that region. We used EcoCrop for the suitability analysis. The modelling exercise assumed that rainfall was not a limiting factor, to allow for the possibility of irrigated production. The statistical data do not reveal where the crop is grown in each NUTS-2 region. The spatial match between the suitability data (pixels of 2.5 arc minutes) and the production data of NUTS-2 regions (polygons that cover many of these pixels) is not known. Therefore, we analysed two extreme cases, a pessimistic and an optimistic one. If we are pessimistic, we would expect that the crop is equally spread over all pixels within each region. Being optimistic, we would expect that the crop is grown in the pixel(s) with the highest suitability value in each region. Analysing both cases, we calculated the *mean* and *maximum* EcoCrop suitability values of each NUTS-2 region and crop combination. Mean suitability refers to the average value of suitability for a crop across all the pixels within that region, whereas maximum suitability refers to the maximum suitability value identified for the same crop across the pixels within the region.

2.5. Analysis of future crop suitability

To analyse future crop suitability and inform decision-makers, we took two different perspectives. Firstly, we analysed the expected change in crop suitability. Secondly, we analysed which crop can be expected to be the most suitable in each area under present and future conditions (2050s).

In the first analysis, we calculated the percentage change in crop suitability for the analysed EU-28 countries from the EcoCrop outputs for the baseline and future climates. Mean values were calculated for each crop in each country. Aggregated national suitability was defined from the mean suitability values for all cropland surface pixels within national boundaries (Ramankutty et al., 2008). This calculation was replicated for all the 30 GCMs runs of the model. We also identified whether climatic or soil pH conditions were the limiting factor in future suitability across the EU-28 analysed countries. The limiting factor was identified for all cropland surface pixels within national boundaries, with the modal value taken to define the national limiting factor.

In a second analysis, we identified the best baseline and future crop options for each cropland surface pixel. For this analysis we assumed rainfed crop production. By assuming rainfed production, we focused the analysis on identifying production areas where the crops would not be competing strongly for scarce water resources. This matches our main interest, which is to identify crops that have potential as meat replacements to reduce environmental impacts. In addition, crop irrigation in Europe is not expected to expand greatly in the future (Alexandratos and Bruinsma, 2012). This implies that most expansion of these crops will be into non-irrigated areas.

To determine which was the most suitable crop, we created a "stack" of layers in the raster package, with each layer representing a different crop. We then calculated which layer had the highest suitability value. In defining future ideal crop options, a similar approach was applied. However, we initially developed a crop suitability layer that included results from all 30 GCMs. For this, we extracted the mean suitability value for each land surface pixel from a stack of the 30 GCM specific crop layers. This was repeated for each crop. These mean suitability layers were then stacked. Using these mean crop suitability layers, we repeated the same methodology as for the current ideal option.

2.6. Sensitivity analysis

In section 2.4 we described one way to assess the validity of the suitability modelling results, which was to compare with observed values for current crop distributions. This could only be done for 5 of the 13 crops. Complementing this analysis, we performed a sensitivity analysis of the EcoCrop model. Previous analyses have shown that the EcoCrop model has limited sensitivity to parameter changes in other contexts (Ramirez-Villegas et al., 2013; Manners and van Etten, 2018). To support the validity of the results, we analysed the sensitivity of EcoCrop outputs to changes in temperate, precipitation, pH, and crop cycle length.

We altered the climate and soil adaptation parameter ranges defined by FAO (2016), varying them downwards and upwards so that the correct parameter value is probably found within the resulting range (Table 2). Following Manners and van Etten (2018), we varied the maximum and minimum temperature parameters by -/+2 °C, altered the range of precipitation by -/+ 25%, varied the permissible range of

Table 2
Sensitivity scenarios representing crop parameter changes.

Change in temperature or precipitation	Crop Cycle +1 Month	Crop Cycle -1 Month
Minimum temperature +2 °C	*Tmin + 2C + 1 m*	*Tmin + 2C − 1 m*
Minimum temperature –2 °C	*Tmin-2C + 1 m*	*Tmin-2C − 1 m*
Maximum temperature +2 °C	*Tmax + 2C + 1 m*	*Tmax + 2C − 1 m*
Maximum temperature –2 °C	*Tmax-2C + 1 m*	*Tmax-2C − 1 m*
Precipitation +25%	*Pre + 25% + 1 m*	*Pre + 25% − 1 m*
Precipitation –25%	*Pre-25% + 1 m*	*Pre-25% − 1 m*
pH + 25%	*pH + 25% + 1 m*	*pH + 25% − 1 m*
pH -25%	*pH-25% + 1 m*	*pH-25% − 1 m*

pH values by -/+ 25%, and changed the crop cycle length by -/+ 30 days. We combined changes to crop cycle length with the other three parameters, to observe potential interactions. In total, 16 tests of sensitivity were performed (Table 2).

To assess how sensitive suitability is to the changes in Table 2, we analysed the difference in crop suitability outputs in each EU country under the baseline parameters (FAO, 2016) with the outputs derived from the scenarios. Following Manners and van Etten (2018) we categorised whether suitability increased, decreased, or remained the same (neutral).

3. Results

3.1. Current geographic distribution and climate suitability of protein-rich crops

Fig. 1 show the relationship between the agro-ecological suitability for 5 protein-rich crops and the observed patterns of their share of land (as a percentage of all protein-rich crops present). To make clear what pattern would be expected of current protein-rich crop distributions, we display a dashed line between the origin of the graph (zero production share and zero suitability) to the right upper corner of the graph (maximum suitability, top value share) (Fig. 1). If suitability is considered a limiting factor, most points are expected under this line and a few above it. If points were not limited by this line at all, it would falsify our hypothesis that climate suitability, as determined by EcoCrop, limits observed crop production. We also include quantile regression lines (red line), derived from regressions of the 95th quantile of crop distribution and suitability values for each crop. Regression lines are only plotted if a relationship was found to be significant ($p < 0.05$).

For all crops the majority of points is below the dashed line, showing the hypothesised asymmetric relationship between suitability and production. In most cases crop distribution is far below what may be expected from its suitability, however. Buckwheat (Fig. 1g and 1 h) is a particularly good example of this, with production only occurring in regions with near perfect conditions, with its distribution being far below what may be expected. This evidences that other factors, beyond climatic suitability, are important when it comes to protein-rich crop choice.

Fig. 1 also displays that at the 95th quantile of crop distributions, climatic suitability is significantly related to distribution for soybean and faba bean (max and mean suitability), and pea under mean suitability. Other relationships were found to be marginally insignificant at the 95th quantile of suitability results, but in most cases this is because crop production occurs only under optimal conditions, limiting the range of suitability values for the regression analysis.

3.2. Future protein-rich crop suitability

Outputs from the extended EcoCrop model demonstrate that climate change could have widespread impacts on the suitability of protein-rich crops across the EU (Fig. 2). Particularly vulnerable to future climates are the traditionally important legume-producing countries, including Spain, France, and Italy. Each of these countries will see average suitability changes for common bean (-0.07 to -0.01), faba bean (-0.03 to -0.01), chickpea (-0.04 to -0.01), and lentil (-0.03 to -0.01). In contrast, in Denmark, the Netherlands, and the UK, suitability changes are positive for common bean (+0.02 to +0.08), faba bean (+0.02 to +0.04), chickpea (+0.02 to +0.07) and lentil (+0.03 to +0.06). These geographically divergent patterns are similar for crop species like amaranth, quinoa, and Andean lupin. Full tabulated results are available in Online Resource 3.

The results of crop suitability changes (Fig. 2) suggest how different regions of the EU are differentially affected by climate change. The results also highlight the variation in suitability outputs for each country under the specific conditions of each of the 30 GCMs. The results display that suitability will largely increase in northern and central Europe and decrease in most of the south. Fig. 2 also shows that soil pH had a limited effect in defining crop suitability. Suitability of quinoa and blue lupin in Finland and Sweden were found to be mainly limited by this parameter in 2050 (shown as green fill in the boxes of Fig. 2). Where climate suitability is no longer the limiting factor, crop suitability is highest on non-acidic soils.

Fig. 3 shows the spatial patterns of future suitability for selected crops across the EU. These results present average suitability values from the 30 GCM runs. In 2050, areas identified with high suitability for protein-rich crops were concentrated within Adriatic countries, alpine regions (northern Italy, Slovenia, southern Germany, and Eastern France), and northwestern Europe. However, in some of these regions suitability for a number of crops was modelled to decline (e.g. faba bean and chickpea in Croatia). Further, quinoa and to a lesser extent blue lupin were found to have high suitability across a range of environments. High quinoa suitability was observed from the Atlantic coast of Portugal, to the Eurasian Steppe. In contrast, regions highly suitable for soybean are almost exclusively concentrated in the Adriatic, while less suitable areas are seen in southern Germany and Ireland.

Under the baseline conditions (Fig. 4), quinoa was found to be the most suitable crop across almost 70% of European arable land followed by: blue lupin (23%), common bean (4%), and white lupin (1%). However, by 2050 (Fig. 4b) a less diverse cropping structure is observed, suggesting the role of climate change. Quinoa dominates, representing the most suitable crop in 80% of European arable land, together with blue lupin (8%), common bean (6%), and white lupin (3%). Further, multi-crop options were identified, representing a suite of crops with the same suitability in that pixel.

3.3. Sensitivity analysis

The full results of the sensitivity analyses are found in Table 3. The table displays how changes in the parameters for each test effect how suitability responds under present and future conditions. Suitability is characterised into three categories, increase, neutral, and decrease. These categories represent changes from present climatic conditions to future conditions. Table 3 shows how changes to parameters can alter these categories, with five categories developed to highlight how the parameter changes can alter suitability, from the baseline to future. The results display the number of crop country combinations (e.g. "quinoa suitability in Sweden") affected by the parameter changes, based on average national suitability values for each crop.

The results demonstrate that under all tests, the greatest number of changes to suitability in crop-country combinations (e.g. "quinoa suitability in Sweden") were seen for the *pH*-25% + *1 m* test, where 32% changed, with 31% changing for the *Tmin + 2C + 1 m* and the *Pre* + 25% − *1 m* tests. Complete changes in suitability outputs (increase to decrease or decrease to increase) represented 21% of all crop-country combinations in the worst case. The most extreme cases are shifts from decrease to increase. If parameter values are far from those in the EcoCrop model, the risk of having a pessimistic model is higher

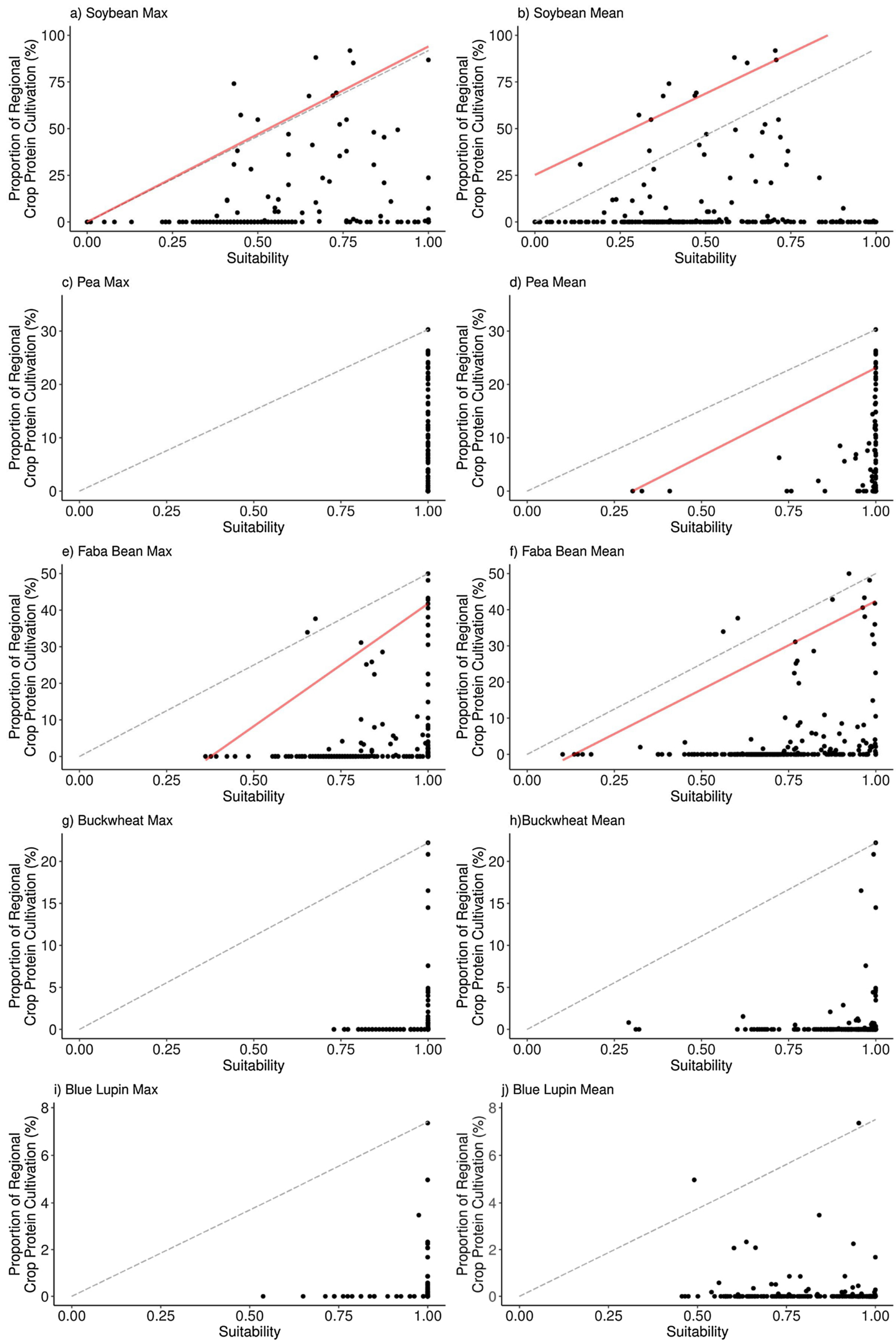

Fig. 1. Relationship between current crop distribution and modelled maximum and mean crop suitability for EU-28 NUTS-2 regions with available data. Quantile regression lines (red line), derived from the 95th quantile are plotted if crop distribution and climatic suitability relationship was significant ($p < 0.05$). Dashed line represents non-statistically supported theoretical expected relationship between distribution and suitability.

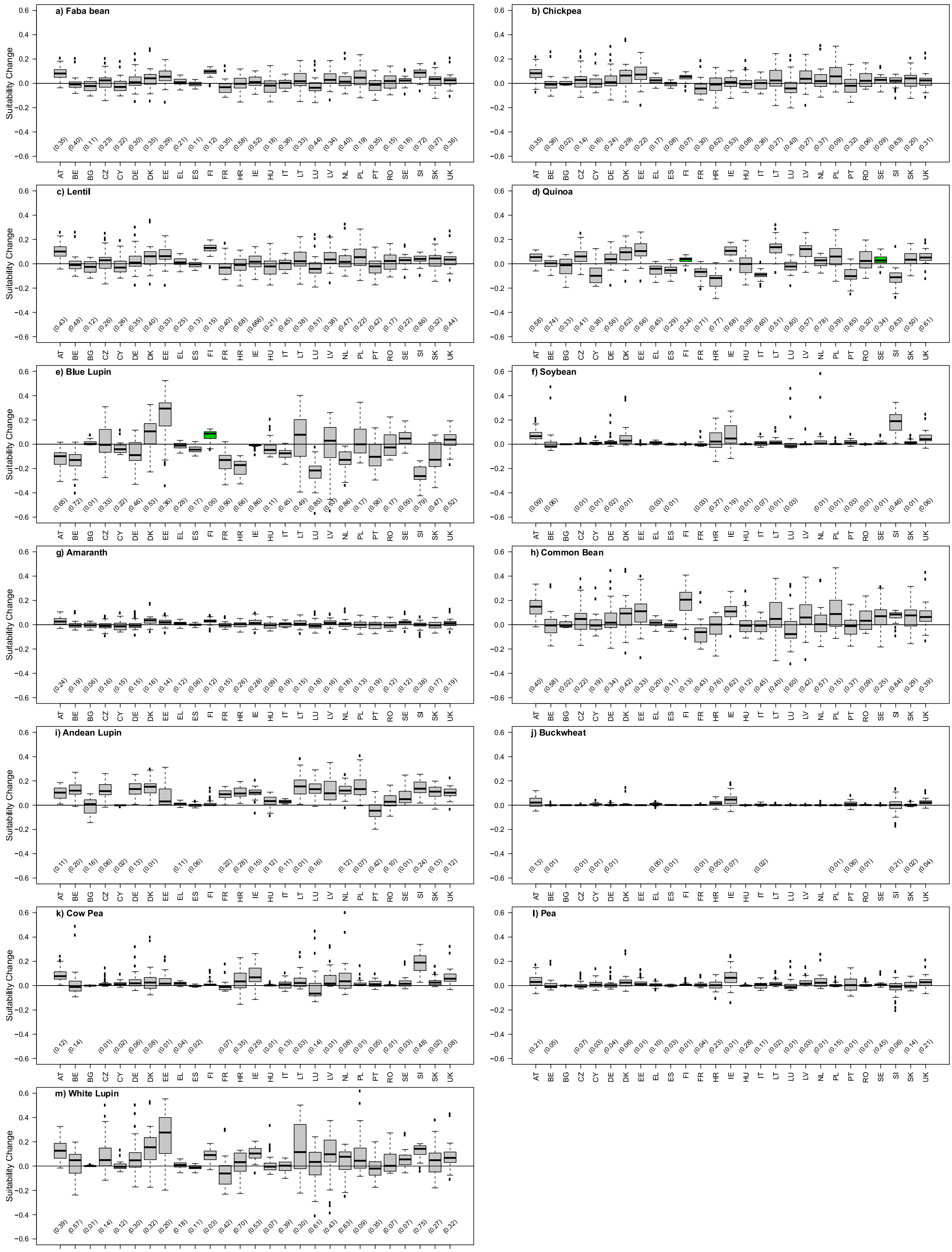

Fig. 2. Changes in suitability from baseline (1970–2000) to future (2050s) climates. Boxes represent results of all 30 GCMs under the RCP4.5 climate scenario. Values in brackets demonstrate national suitability under the baseline conditions. Box colours represent the limiting factor of suitability for each crop (grey climatic conditions and green soil conditions).

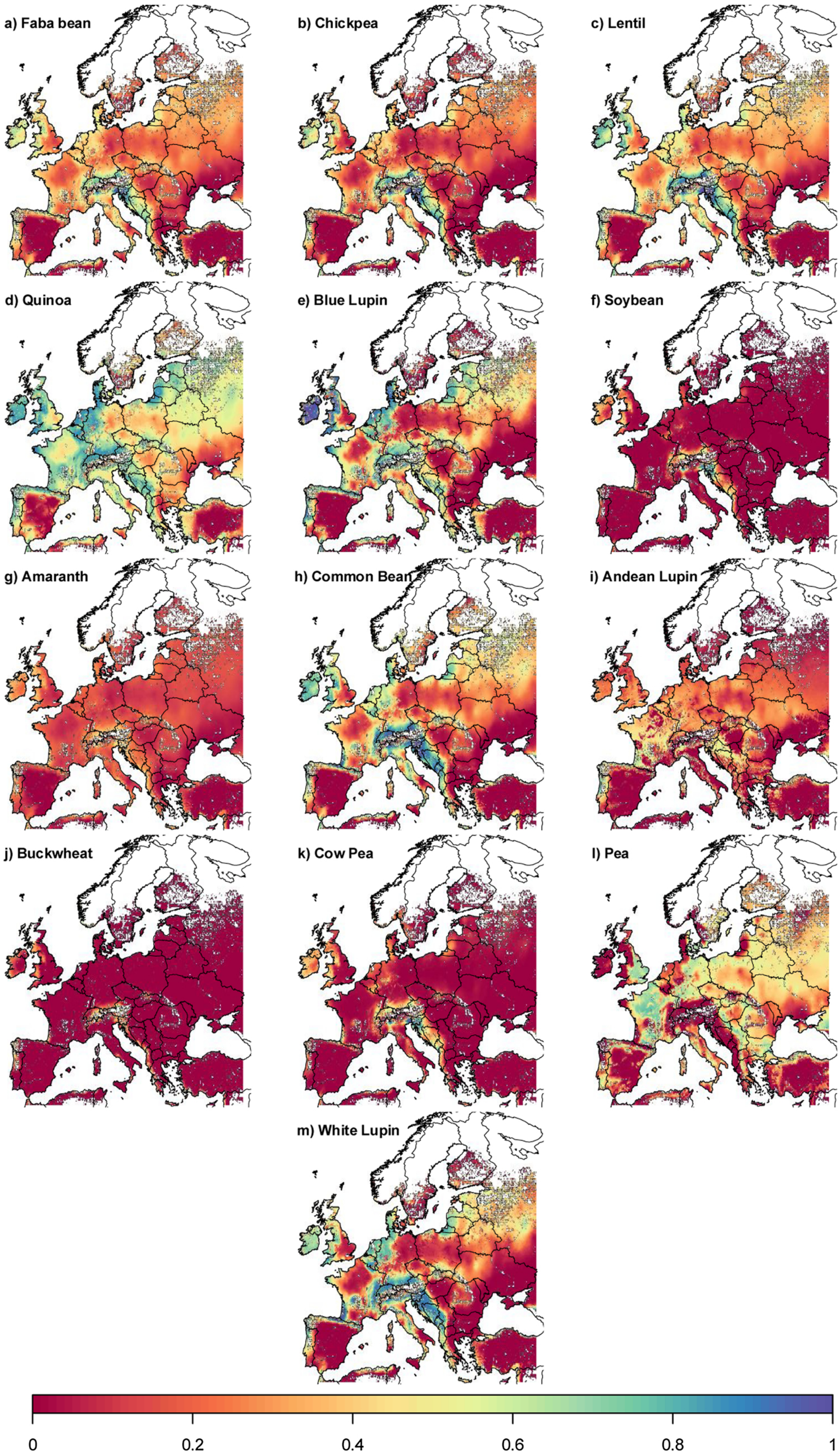

Fig. 3. Geographical representation of average future suitability generated from 30 GCMs under RCP4.5. 0 (red) represents unsuitable conditions, and 1 (purple) suitable conditions. White pixels represent lands not cultivated under the baseline.

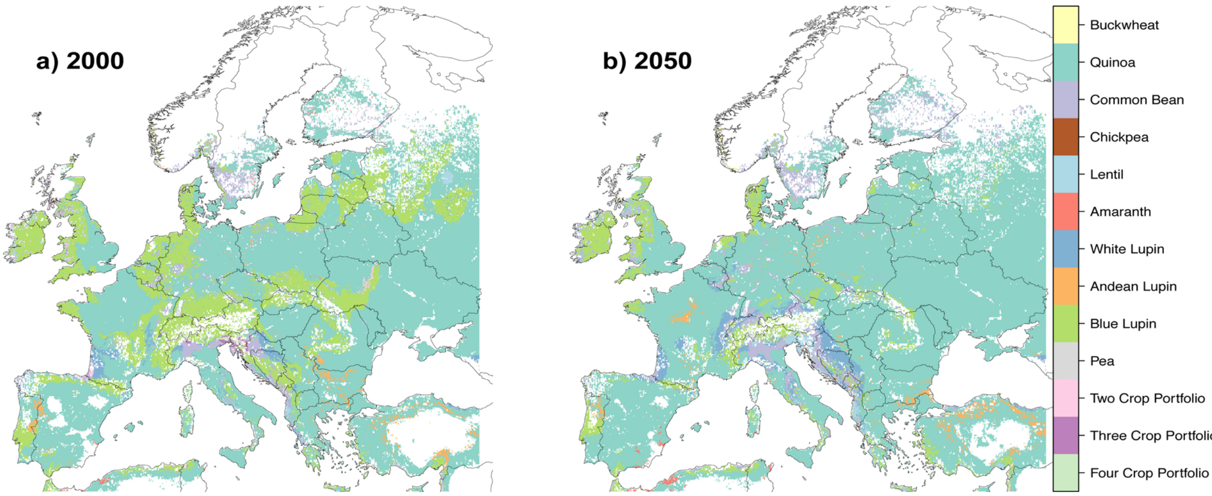

Fig. 4. Suitable protein-rich crop options under baseline and future climates conditions.

than having an optimistic model.

4. Discussion

We performed two exercises to evaluate if the EcoCrop model can make meaningful predictions of crop suitability under climate change. The first exercise showed that suitability determined with EcoCrop corresponded well with current distribution patterns of 5 protein-rich crops in Europe. Even though we were not able to do this exercise for all crops, these results confirm that EcoCrop is able to make a reasonable representation of important limiting factors that influence the broad cross-continental pattern of crop environmental adaptation. Secondly, we performed an analysis to determine the sensitivity of the EcoCrop model to uncertainty in the crop adaptation parameters of the model. This sensitivity analysis is important, because we do not know if the parameters are very precise, as we could not calibrate the parameters of EcoCrop model with distribution data (cf. Ramirez-Villegas et al., 2013). The sensitivity analysis shows that at country level, in the worst case a full reversal of the climate trend occurred for 21% of the crop-country combinations. The sensitivity is within reasonable limits, even though it is higher than in a world-wide analysis of a broad range of major crops (Manners and van Etten, 2018). Therefore, we expect that the broad trends revealed by our analysis will hold against uncertainty in crop model specification, but we should not overinterpret the results for individual crops and subnational units. A remaining source of uncertainty is climate modelling. Diminishing this uncertainty will rely on improved climate modelling. Uncertainty will always remain substantial due to the inherent limits of predictability of climate systems. Future analyses could address this uncertainty in a more explicit way through scenario analysis to inform scenario planning (Vervoort et al., 2010; Vermeulen et al., 2013; Star et al., 2016). A limitation of this paper is that it focuses on GCM-averages of a single climate scenario.

Our results show that climate suitability is a relevant limiting factor of crop production that shapes the current geographic distribution of protein-rich crops in the EU. Other factors will also play a role in determining cropping, but where suitability is low for a given crop, its production is invariably low as well. The crop production is only high where crop suitability is also high. This suggests that the EcoCrop modelling results are relevant. As these suitability values are affected by climate change, decision-makers should take into account how changes in suitability will constrain future production of protein-rich crops, especially where crop distributions push against the envelope of suitable areas. Our results also highlight that in many regions protein-rich crops are not included in crop portfolios, despite ideal suitability. Such findings implicate the impacts of competition in productive environments for protein-rich crops. In the case of soybean, high

Table 3
Sensitivity analysis results. Crop-country suitability changes observed under the conditions of each of the sensitivity scenarios.

Scenario	No Change		Increase to Decrease		Decrease to Increase		Neutral to Increase or Decrease		Increase or Decrease to Neutral	
	Crop Country Combinations	%	Crop Country Combinations	%	Crop Country Combinations	%	Crop Country Combinations	%	Crop Country Combinations	%
Tmin + 2C + 1 m	242	69	7	2	65	19	21	6	16	5
Tmin + 2C − 1 m	271	77	8	2	31	9	14	4	27	8
Tmin-2C + 1 m	277	79	17	5	29	8	19	5	9	3
Tmin-2C − 1 m	270	77	34	10	12	3	13	4	22	6
Tmax + 2C + 1 m	275	78	8	2	36	10	20	6	12	3
Tmax + 2C − 1 m	300	85	12	3	8	2	12	3	19	5
Tmax-2C + 1 m	276	79	15	4	29	8	20	6	11	3
Tmax-2C − 1 m	291	83	19	5	6	2	13	4	22	6
Pre + 25% + 1 m	266	76	4	1	38	11	14	4	29	8
Pre + 25% − 1 m	242	69	13	4	24	7	15	4	57	16
Pre-25% + 1 m	246	70	23	7	50	14	26	7	6	2
Pre-25% − 1 m	263	75	31	9	17	5	28	8	12	3
pH + 25% + 1 m	266	76	17	5	29	8	21	6	18	5
pH + 25% − 1 m	272	77	32	9	8	2	12	3	27	8
pH-25% + 1 m	237	68	7	2	61	17	22	6	24	7
pH-25% − 1 m	257	73	18	5	31	9	14	4	31	9

suitability across regions of southern Europe was not associated with high production. In many cases pea was produced in these regions, despite identical suitability, with similar patterns seen for faba bean and lupin. This may suggest the influence of other, non-climatic, drivers in crop-choice in these regions. These results highlight that such competition and the diversity of cropping options may be beneficial as climates increasingly change. Farmers could increasingly shift cropping choices to crops better adapted to new climatic conditions (Seo and Mendelsohn, 2008).

The outputs of this work have demonstrated that climate change has a divergent impact on protein-rich crops, which is also true for European agriculture in general (Zabel et al., 2014). Some countries benefit while others incur losses. The overall pattern of our findings follows that described by Salon et al. (2011). Cool-weather legume species (faba bean, lentil, lupins, pea, and chickpea) are particularly sensitive to abiotic stresses intensified by climate change, while warm-weather legumes (cow pea and soybean) are less affected. The suitability of cool-weather species declines in southern parts of Europe and increases in northern parts. In the north, climate change was found to represent an opportunity for many protein-rich crops. The results also demonstrate the striking potential of quinoa and certain lupin species in many regions. With this finding we confirm and expand the findings of some crop-specific studies (Ruiz et al., 2014; Lucas et al., 2015). There is much potential for expansion of protein-rich crop production beyond current crop distributions. For example, there are many opportunities in Finland, as indicated by Stoddard et al. (2009). Southern Europe will experience a reduction in the suitability of culturally important species. This pattern is consistent with previous studies (FAO, 2012; Valverde et al., 2015; Ramirez-Cabral et al., 2016). For all areas there are old and new crops that provide protein-rich meat replacement cropping options for future European agricultural systems.

Geographically differentiated planning, research, and breeding strategies could assist in taking advantage of the positive changes to suitability in northern Europe, while addressing the reductions in southern Europe before they become too extreme. Research realignments may be needed across southern Europe to address the stress-related sensitivity of certain protein-rich crops. Agricultural research and development investments could be shifted towards those crops that are likely to be less vulnerable to climate change in given areas (Manners and van Etten, 2018). Investments will need to compensate for a lag in agricultural research for climate adaptation. On the other hand, increased research could take advantage of the largely unrealised potential of many protein-rich species to adapt to more stress-tolerant varieties, tapping landrace genetic diversity (Daryanto et al., 2015; Cowling et al., 2017), and the wider gene pool of crop wild relatives (Kwak and Gepts, 2009; Berger et al., 2012). Breeding could mitigate the expected distribution shifts by focussing on the specific limiting factors to develop more stress-tolerant varieties, a strategy that is likely to have long-term benefits (Considine et al., 2017). Our findings could be used to encourage policies for promoting climate-proof protein-rich crops as replacements of animal products in human diets.

5. Conclusions

This analysis found climate suitability to be a relevant limiting factor of protein-rich crop production, shaping the contemporary geographic distribution of protein-rich crops across the EU. It has also provided insights into the potential effects of climate change on these crops, exhibiting the divergent impacts of climate change across the continent. Cool-weather legume species were found to be particularly sensitive to abiotic stresses intensified by climate change, while warm-weather legumes less so. The suitability of cool-weather species declines in southern parts of Europe and increases in northern parts. In the north, climate change may represent an opportunity for many protein-rich crops. There is much potential for expansion of protein-rich crop production beyond current crop distributions. These findings could be applied to inform policy-making addressing the impacts of climate change on protein-rich crops. Geographically differentiated planning, research, and breeding strategies could assist in addressing these changes.

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