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Are agricultural researchers working on the right crops to enable food and nutrition security under future climates?

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ABSTRACT

This study examined how crop-specific agricultural research investments can be prioritised to anticipate climate change impact on crops and to enable the production of more nutritious food. We used a simple crop modelling approach to derive expected future changes in regional climate suitability for crops. To determine if different starch-rich and pulse crops are currently underresearched or overresearched, we examined the global relation between crop-specific research output (number of publications) and the total nutrient output available for human consumption. Our analysis shows that current research investments are mostly associated with the current energy output of crops. Other things equal, investment levels tend to be slightly lower for crops better adapted to future climates and tend to decrease as crop nutrient richness increases. Among starch-rich crops, maize, barley, and rice receive substantially more research investment than justified by their current nutrient output. Sweetpotato, potato, and wheat show substantial current research deficits. Sweetpotato is most strongly underresearched in regions with improving climate suitability. For potato, research deficits occur in regions where these crops will experience less suitable climate conditions. For wheat, the deficits are distributed equally across regions with negative and positive climate effects. Three crops are significantly over-researched, namely maize, rice, and barley. Among pulses, cowpea, and lupin are generally overresearched. Common bean is highly underresearched, but these deficits concentrate in areas where it will likely suffer from climate change. Lentil, broad bean, and chickpea are underresearched, with deficits concentrating in regions where these crops will tend to benefit from future climates. Agricultural research investment allocations will need to consider additional factors not taken into account in this study, but our findings suggest that current allocations need re-consideration to support climate adaptation and enhance healthy human nutrition.

1. Introduction

There is broad agreement that climate change represents a major challenge to the global food system. The IPCC (2014) suggests that from 1960 to 2013 climate change had more negative than positive impacts on food production systems. Geographically, climate impacts on agricultural production are highly disparate (IPCC, 2014; Leclère et al., 2014; Yang et al., 2015; Dono et al., 2016). At the same time, agriculture is under pressure from the growing demand for agricultural products due to global population growth (Ziervogel and Ericksen, 2010; Godfray et al., 2010). Even under current conditions, agricultural systems fail to address malnutrition of more than 2 billion people who suffer from micro-nutrient deficiencies (International Panel of Experts on Sustainable Food Systems (IPES-Food, 2016). This is partly due to the insufficient production levels of nutrient-rich crops required for healthy human nutrition (Siegel et al., 2014).

While there is agreement that climate change and malnutrition present a double challenge to the global food system, there is less agreement about how crop-related R&D efforts should respond. Predictive studies have attempted to achieve insights into future change. For example, a large number of studies have tried to determine the expected yield change in major food crops and specific agronomic measures to counteract these impacts (Lobell et al., 2011; IPCC, 2014; Lobell, 2014). These studies are likely to have limited practical value to set R&D priorities as they try to hit a moving target. In many cases, other changes will override modelled changes. As climate change progresses, farmers will tend to move away from crops with increasingly low yields and substitute them with other crops better adapted to the

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new conditions (Seo and Mendelsohn, 2008; Burke et al., 2009). Climate change will also affect crop production indirectly by stimulating migration and off-farm activities, which will in turn affect the availability of labour and capital for crop production and eventually farmers' crop choice. On top of this, there are other policy demands, especially on the quality of food, that call for an increased focus on more nutritious crops, beyond the absolute yield of the major energy-providing crops (Pingali, 2015). An increasing global population and changes to consumer demands will also have to be accounted for by future agricultural systems (e.g. Vranken et al., 2014).

Given these wide-ranging changes, agricultural research should prioritize investments from a wide, systemic perspective. Crop-specific R&D is a long-term investment and should focus on the production systems and crops that are deemed to be most relevant in the long term. One of the first steps in priority setting for crop R&D should therefore focus on strategic investment allocations across food crops. There are a number of choices to make in order to set priorities. Should a currently important crop that is losing terrain to climate change be propped up? Or should R&D instead focus on preparing the terrain for alternative crops that are expected to win under climate change and have high potential for human nutrition? These choices are strategic and will involve complex coordination with other types of policies and business strategies.

This study provides a first input to set priorities for crop-specific agricultural R&D investments. Decision-making on agricultural R&D investment is not subject to a straightforward optimisation and it does not address a well-characterised problem. It is probably best characterised as a "pathway" in search of negotiated, interconnected solutions (Wise et al., 2014). There is path-dependency and reflexivity in this type of decision-making, as R&D investments will affect crop adaptation and crop adaptation will in turn affect the opportunities for R&D investments. Decision-making processes will involve negotiations, value-based decisions and the creation of a shared vision, which are difficult to predict. Even so, decision-makers need to take into account those aspects of the problem that are not easy to change and that provide relatively hard boundaries that delimit the solution space. Also, decision-makers need to consider the widest possible range of options, before closing in on a subset of solutions. Therefore, we do not suggest an optimal allocation of R&D investment across crops, but rather provide easily interpretable information that should be combined with other considerations in a broad-ranging discussion among stakeholders to set priorities.

As a first element, we provide a relatively simple, transparent indicator of the direction of change expected from climate change that can be calculated for all crops, including "data-sparse" ones (which are often ignored in climate impact studies). We also explored the uncertainty in the information provided. First, we determined for any given region of the world which crops will increase and decrease the geographical extent of their *potential* niche. In reality, their expansion or contraction will depend on many other factors, including crop-specific agricultural R&D investment itself. Even so, growing niche-contracting crops will likely incur increasing costs to offset the effects of climate change. Costs may include the cost of breeding for stress tolerance, increased need for irrigation, increased crop losses, increased costs of crop insurance, or reduced resource use efficiency due to lower average yields. Our simple indicator can be considered as an indication of the effort needed to keep a particular crop in place.

The other element to be considered in decision-making is objective information on the relative importance of each crop for food and nutrition security. The rationale is that the relative importance of crops is a key factor to allocate R&D funds, following the concept of "congruence" (Gryseels et al., 1992). We compared the crop-specific agricultural research output per crop for each region with their relative importance to determine if crops are currently underresearched or overresearched. In this analysis, our measure of relative crop importance was current nutrient output. This follows the argument made by Pingali (2015) that crop research investments should shift from the Green Revolution focus on energy output to a focus on human nutrition (also, see International Panel of Experts on Sustainable Food Systems (IPES-Food, 2016). Pingali (2015) suggests that this implies a shift from staple crops to fruits and vegetables. However, also within starch crops and pulses this would imply a shift in research priorities. Predicting future consumption is exceedingly complicated, especially for minor crops. Another issue is that shifts in consumption will depend on R&D investments, leading to circular causality. To steer free from these issues, we focused on current nutrient output values, which serve to benchmark research intensity levels, against which future investments can be assessed. We synthesised the results in ways that facilitate interpretation for priority setting, considering simultaneously both climate adaptation and human nutrition.

2. Material and methods

2.1. Regions and crops

We report our results by broad geographic regions. We used the regions as defined by Brummit (2001), dividing the globe into 50 plant distributional regions (Fig. 1). We selected this scheme, because (1) it is an international standard for plant geographical distributions, (2) it follows political boundaries (countries and large subnational areas), which facilitates linking the areas with census and bibliometric data, (3) the number of regions can be represented in global overview tables

Fig. 1. Map of the plant distribution regions used in the study, adapted from Brummit (2001).

and small maps. We excluded the Antarctic for this study, as no crops are grown there. Due to their small agricultural land area, we also excluded Macaronesia, Middle Atlantic Ocean, North-Central Pacific, Northwestern Pacific, Southwestern Pacific, Subantarctic Islands and Subarctic America.

We focus on two main categories of food crops: grains, tubers and roots, bananas and plantains (“starch crops”), and “pulses”. We excluded other categories as census data for fruits and vegetables are difficult to compare across continents and sugar and oil crops have fewer crops in each group.

2.2. Crop suitability modelling

Crop suitability was modelled using climate data for current and future conditions in order to determine for each crop in each region if suitability will increase or decrease. The current data (1970–2000) were taken from WorldClim (Fick and Hijmans, 2017). We used monthly data for precipitation, minimum temperature, and mean temperature as inputs into the crop model. Data of a 5 arc minute resolution were aggregated to a resolution of 20 arc minutes.

Projected future climate data were taken from the CCAFS database (Ramirez and Jarvis, 2008). These data were previously downscaled, as described by Ramirez and Jarvis (2010). We used all 30 available General Circulation Model (GCM) projections for the IPCC RCP 4.5 scenario, with a model run for each projection. These projections estimated climatic conditions for the year 2050. Again, we used monthly data for precipitation, mean temperature, and minimum temperature. Data with a resolution of 5 arc minutes were aggregated to 20 arc minutes.

To assess the regional suitability of each crop, the EcoCrop function of the R package *dismo* was used (Hijmans et al., 2001; Hijmans and Elith, 2012). EcoCrop is a simple model that evaluates the suitability of a given environment for a crop by comparing monthly temperature and precipitation data with crop-specific admissible ranges. The EcoCrop model is named after the homonymous database, maintained by the FAO (FAO, 2012). We used the data from this database to provide data to our model. We did not use the data provided within *dismo* (Hijmans and Elith, 2012), which stems from a previous version of the FAO EcoCrop database.

EcoCrop gives a first approximation of climate change impacts across crops where more detailed crop modelling results are difficult to obtain. Ramirez-Villegas et al. (2013) found for sorghum that the EcoCrop model predicts suitability well. Jarvis et al. (2012) determined the change in growing suitability due to climate change for seven staple crops across Africa with EcoCrop. Applications of EcoCrop have shown that the results are consistent with other modelling techniques (Ramirez-Villegas et al., 2013; Vermeulen et al., 2013). EcoCrop only considers average abiotic environmental conditions and ignores the presence of pests, disease pressure, soil conditions, and climatic variability. Ramirez-Villegas et al. (2013) discuss the limitations of the model in further detail. In this study, we use EcoCrop to produce a very general indicator of climate change impact: the sign of change in suitability for given crops in very broadly defined regions (following Bellon and Van Etten, 2014). We have further decreased the probability of misidentification by providing slightly conservative estimates of crops that would expand or contract their suitable range under climate change (see section 2.5 below).

We offer a very brief overview of the EcoCrop model as implemented in *dismo* (Hijmans and Elith, 2012). A more detailed description of the computations behind EcoCrop are given in Appendix A ‘EcoCrop Model Computation’. In calculating crop suitability, EcoCrop simulates 12 crop cycles starting in each month of the year. For each cycle, it determines the suitability for crop growth by evaluating to what extent the seasonal climate falls within crop-specific thresholds of maximum and minimum temperature and rainfall (if the crop is not irrigated). It then takes the maximum suitability value of the 12 crop cycles. The model gives a final suitability indicator value between 0 (unsuitable) and 1 (suitable). If the value is between 0 and 1, the crop cycle includes a period with a permissible yet suboptimal temperature or it receives too much or too little rain in the optimal growth period.

Crop suitability was calculated with the data for present and future climates. We applied EcoCrop to each grid cell with cropland (Ramankutty et al., 2008). For each grid cell, the resulting crop suitability indices were multiplied by the total area of recorded cropland in hectares. The results were then summed by region for each crop and each data source (WorldClim and each of the GCMs). The use of the 2000 cropland data (Ramankutty et al., 2008) for the future area calculation does not take into account the potential future emergence of new cropland areas due to climate change or other factors. Porfirio et al. (2017) analysed the potential impact of climate change on the global geographical distribution of cropland in 2100. They projected changes of up to 10% in areas not currently associated with agriculture, including arid and boreal regions. Smith et al. (2010) suggest that global croplands could expand between 6–30% by 2050 due to other (non-climatic) drivers. The potential expansion of individual crops is therefore conservative for higher latitudes to the degree that more land is taken into agricultural use at the expense of other types of land use, especially boreal forests. Even though this effect will affect the magnitude of change, it will not invert the sign of change (positive or negative) of crop suitability change. Crops that are now at their climate limits at high latitudes will become more fully suitable in these areas, so they will show a positive change. Since we focus on the sign (and not the magnitude) of change, this is not a major source of uncertainty for our study. Contraction of agricultural land due to climate change, on the other hand, is even less problematic, as this would correspond to a decreasing suitability of the crops currently grown there, as modelled by EcoCrop. Hence, in tropical and subtropical regions, where some contraction may occur, our approach does not yield substantial distortions.

After obtaining the average weighted suitability shifts, we summarised the results by comparing WorldClim outcomes with those of the different GCMs. If 16 out of the 30 GCMs, representing 50% +1, agreed that the suitable area for a given region will increase for a given crop, the crop-region combination is placed in the “positive climate impact” category, if 50% + 1 GCMs agree on a decrease the crop-region combination is in the “negative climate impact” category. The remaining crop-region combinations are categorised as “neutral climate impact”.

2.3. Sensitivity analysis of EcoCrop results

The accuracy of crop models, like EcoCrop, relies on the quality and validity of their parametrisation (Makowski et al., 2006). The EcoCrop parameter values used in this analysis behave well in other studies (see Section 2.2 above). Even so, it is prudent to analyse the sensitivity of crop suitability outputs to the parameters of EcoCrop to assess the robustness of the analysis. To perform the sensitivity analysis, parameter changes were made to the temperature, precipitation, and crop cycle length data derived from FAO (2012).

We chose variations creating ranges within which the correct parameter value is likely to lie. We varied the maximum and minimum temperature parameters by +/- 2°C; changed the permissible range of precipitation by +/- 25%; and changed the crop cycle length by +/- 30 days. In total, 14 sensitivity tests were performed, with temperature and precipitation sensitivity tests combined with crop cycle length changes to explore possible interactions, with changes to crop cycle length also analysed independently (Table 1).

To gauge the sensitivity of suitability to these changes, we analysed the difference between the regional suitability outputs for each crop under the baseline parameters from FAO (2012), with the outputs from the sensitivity test parameters. The changes were categorised as whether suitability increased, decreased or remained the same.

Table 1
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*
No change	*+ 1 m*	*− 1 m*

2.4. Nutrient output values

Regional total crop production values were taken for each crop (FAO, 2017) to obtain an index of output per region. These values were then weighted by the proportion of crop quantities available as human food, derived from the FAO´s Food Balance Sheets (FAO, 2018a). To develop these values, the amount of each crop available as food was divided by domestic supply for that region. In cases where individual crop food data were not available (e.g. quinoa and lentils), aggregated data (e.g. "cereals, other" and "pulses") were used. We focused on current domestic supply available as food.

These weighted crop harvest output data were then used to estimate regional nutrient output indices for each crop. Nutrient output was calculated as the total nutrient rich foods index (NRF9.3) (Fulgoni et al., 2009) using data for macronutrient, vitamin, and mineral contents of each crop (USDA, 2016), relative to daily reference values (FDA, 2013). Individual crop NRF 9.3 scores were calculated per 50 g of crop. The use of the NRF9.3 index permits a weighting of the crops based upon their nutrient density. NRF9.3 does not include carbohydrates as a nutrient, which may be unfavourable to certain crops. We also tested a version of this index with carbohydrate content, but this did not produce significantly different results. From the nutritional output values of crops, we note the influence of the considerable differences in nutrient density between crops, for example the high nutrient density of sweetpotato, which would have been ignored if we had only classified crops based upon carbohydrate or protein contents.

2.5. Crop-specific agricultural R&D investment benchmarking

We benchmarked crop-specific agricultural R&D investment based on the number of publications and the nutritional output of each crop in each region. Overall, there is a positive correlation between regional nutritional output and the number of publications by region. We made negative and positive deviations from this trend count as evidence for a crop being underresearched or overresearched.

We used Scirus, a (now defunct) free search engine for scientific research literature, to estimate the number of published agricultural research articles on each crop (Elsevier, 2012). We ran searches using the common name of each crop and the name of the countries (or subnational units) in each region in either the title of the publication or the author affiliations. In some cases, more than one common name was used ("maize" and "corn", for example). We limited the scope to the agricultural and environmental sciences to avoid possible confusion (the crop "apple" with the brand "Apple", for example) or publications of less relevance for our goal (in the humanities, for example). We recorded the number of articles estimated by Scirus for the period 2002–2013 to correspond to each crop-region combination. Articles were counted more than once if they correspond to more than one region or crop.

We benchmarked the number of publications on a given crop against the expected number of publications based on the relative share of nutrient output from that crop. We benchmarked regionally and globally. Regional benchmarking is relevant for R&D investments that do not easily spill over from one region to another. Also, it helps to guard against unknown regional biases in publication database. Global benchmarking is relevant if a low R&D investment in one region can be compensated by investments in another region.

To set benchmarks, we used a zero-inflated Poisson generalised linear model with publications as the response variable and ln(total nutritional values +1) and region (a categorical variable which modifies the intercept) as the explanatory variables, while we predicted zero-inflation using the energy score (see below). We took the regression line as the benchmark. To set global benchmarks, we did the same but without the region variable in the linear regression. We calculated for each crop-region combination the difference between the actual number of publications and the regional and global benchmarks. We aggregated the research intensity across regions. To be conservative, only if the research intensity was 1 or more publications below the benchmark, the crop was considered underresearched for that particular region and retained. We then summed the research intensity for each of the underresearched regions. The "regional research deficit" is the sum of regional research deficits using the regional benchmarks. The "global research deficit" is the sum of global research deficits using the global benchmarks.

2.6. Other determinants of crop-specific agricultural research intensity

Our analysis takes nutrient output as its measure of crop importance, as this is the main societal value of crop production (Pingali, 2015, see Introduction). However, current investments may follow other principles, to do with previous policy emphasis on energy provision or the monetary value of crops. Therefore, we explored to what extent these factors influence current research intensity and our approach represents a shift in priorities. We calculated energy output per crop, using crop-specific energy data (USDA, 2016). Also, we calculated the monetary value of crops using producer prices (FAO, 2018b). We also tested if there was a bias in crop-specific agricultural R&D investment against or in favour of crops that increase in suitability under climate change, using the modelling results of the method described in Section 2.2 above. We entered these values as explanatory variables in a zero-inflated Poisson generalised linear model. We used the Akaike Information Criterion to select the best model. The zero-inflation part of the model turned out to be predicted only by the energy output.

2.7. Computations

We performed all analyses in R (R Core Team, 2016), using packages from Table 2.

2.8. Main limitations of this study

To interpret the results of our study, it is important to take into account its main limitations. These limitations are generally due to the

Table 2
R packages used as part of analysis.

Package	Package Function	Authors
dismo	Crop suitability modelling	(Hijmans et al., 2017)
ggplot2	Plotting	(Wickham and Chang, 2016)
grDevices	Plotting and colour manipulation	(R Core Team, 2016)
grid	Plotting and layout manipulation	(Murrel, 2016)
maptools	Reading and handling spatial data	(Bivand et al., 2017)
pscl	Statistical analysis	(Jackman et al., 2017)
raster	Geographic data analysis and manipulation	(Hijmans et al., 2016)
reshape2	Data manipulation	(Wickham, 2016)
rgdal	Geographic data analysis and manipulation	(Bivand et al., 2016)

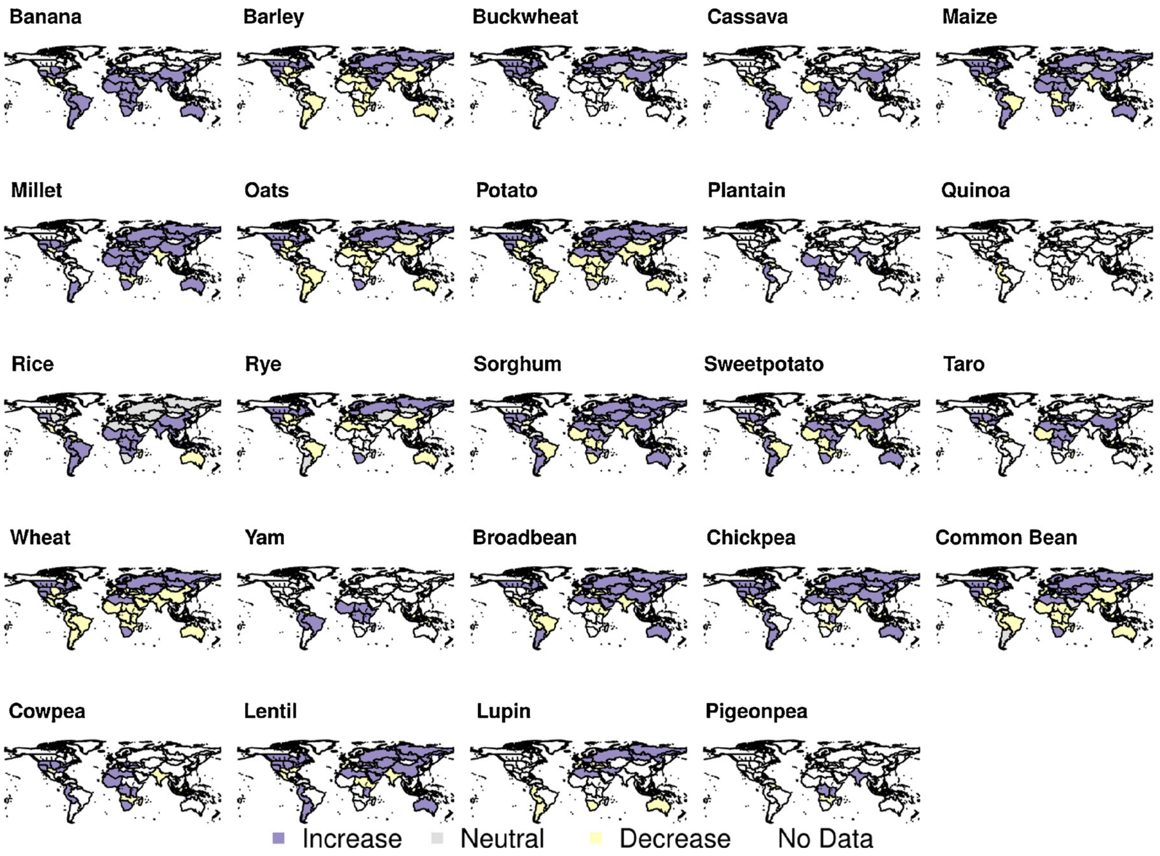


Fig. 2. Crop suitability changes across regions where they are currently present. Crops with suitability increasing across 16 of the 30 GCMs were categorised as increasing, those where no change was seen across the models were categorised as climate neutral and those where suitable area reduced were categorised as decreasing.

sparsity of data available for many of the crops studied and the relatively simple modelling methods we have used. Improved data sets and more refined analyses will hopefully become available to address these limitations.

This study does not perform a detailed calibration of the EcoCrop model for each crop. The EcoCrop model could be calibrated to provide a better geo-spatial characterisation of the impacts of climate change on these species (Ramirez-Villegas et al., 2013). The sensitivity analysis undertaken, however, makes it possible to analyse whether or not the results would drastically change if the parameters of the EcoCrop model were to be refined.

Another important limitation is that the study does not quantify the degree of change in climate suitability of crops, but only categorises crops per region according to the sign of change. This limitation is a result of the lack of reliable, comprehensive data on actual crop distributions on all crops included in this study.

The current study focused only on crops for which global census data is available. However, there is a range of crops that are not included in national statistics in spite of their local importance for human nutrition and that are neglected by agricultural research. We suspect that even though each individual species makes a small contribution at national scale, as a group these species potentially make a substantial contribution in certain locations. The inclusion of these so-called neglected and under-utilised species (NUS) would also aid in providing a clearer picture of future adaptation potential. The potential of these crops is evident in that crops that were only of local importance a few decades ago, such as quinoa, are now getting much more attention and are grown widely (Bazile et al., 2016). However, no global production data is currently available for NUS crops, making it difficult to establish if they are underresearched or not with the method employed here.

Also, the prioritisation on the basis of current research deficits is only done for crops that are present in each region. We do not take into account the possibility of introducing crops into regions in which they are not currently grown. The successful introduction of crops to regions will depend on a number of factors including acceptance by farmers and consumers and initiatives supporting value chain development. Historically, crop introductions have a mixed record of success, but they have been undeniably very important in shaping production systems (Wood et al., 2011). Crop introduction possibilities are therefore important to evaluate in the context of climate change, but are not further considered here.

Another limitation is that the use of scientific publications as a proxy of investment rather than directly using investment values for each crop does not take into account that research may have significant differences in efficiency between crops, in terms of the capacity of converting research investments into publications. This could be resolved with the disaggregation of R&D investments by crop. The International Food Policy Research Institute (IFPRI) provides annual reports on agricultural research spending, but without crop disaggregation (International Food Policy Research Institute (IFPRI, 2016). More disaggregated datasets are needed to provide a more accurate picture of research investments per crop.

Further, only the current nutrient output of food crops is considered. This did not take into account that crop production also contributes to human nutrition through the provision of feed to animal production. The importance of feed crop production is likely to change in the future as regional and global diets transition (Vranken et al., 2014). Also, we did not take into account the fact that the nutritional value of crop products may change as a result of climate change (Myers et al., 2014) or efforts to increase the nutrient density of crops through breeding (*biofortification*) (Bouis and Saltzman, 2017). In spite of the importance of the expected changes in the nutrient density of crops, our analysis assumes that the overall crop portfolios will generally have larger effects in shifting nutrient output. We did some preliminary tests changing a single nutrient value for a crop by a percentage that can be expected from the effect of biofortification. These tests showed that our results are robust to such changes. Nutrient values for each crop are calculated across 9 different nutrients and these values are stable even if one of these values changes by a large percentage. This does not mean, however, that nutrient density of single nutrient is not important. Nutrient output is considered as a one-dimensional variable in our analysis, which does not focus on the complementarity between crops in providing different nutrients or the relative deficit that each crop fills for the actual most critical type of nutrient in human diets. This last limitation would be best addressed through follow-up studies focusing on scenarios of future crop portfolios and diet composition.

3. Results

3.1. Suitability under climate change

In Fig. 2 we present for each crop the modelled impacts of climate change in regions where they are currently present. The results highlight the heterogeneous impacts of climate change across regions and crops. For the majority of crops present in the tropics climate change represents a considerable challenge. Crops present in more northerly and southerly regions are less negatively impacted and often show suitability increases. The outputs also demonstrate how climate change could affect current food staples like maize, rice, and wheat in regions where they are currently important for food security.

3.2. Sensitivity analysis

The sensitivity analysis outputs are reported in Table 3. It shows how many crop-region combinations give a different result if the EcoCrop model is parameterised in a different way (one crop-region combination is for example: “Maize - Middle Europe”). EcoCrop outputs were found to be least sensitive to + 1 m for both starch crops and pulses. Under all tests and for both crop groups, changes in the direction (increase, decrease or no change) of suitability in each crop-region combination were found to be highest for the Pre + 25% − 1 m test. In this case, 16% of starch crop-region combinations and 18% of pulse combinations changed in some direction compared to the baseline. A complete shift in sign of change, from positive to negative or the other way around, was observed in only 1–12% of the crop-region combinations under each scenario.

Even though crop cycle length was determined with a very simple method that does not fully reflect the full range of possibilities, the sensitivity analysis results indicated that the precise crop cycle length parameterisation does not heavily influence the final results. This supports previous findings, which also showed that EcoCrop outputs have limited sensitivity to the parameterisation of crop cycle length (Ramirez-Villegas et al., 2013). Despite this, the interaction between this parameter and others, especially precipitation, did induce greater changes to EcoCrop outputs. However, that the greatest sensitivity was found to be changes to 16% of starch and 18% of pulses crop-regions emphasises the low sensitivity of EcoCrop outputs to parameter specification under the conditions of our sensitivity analysis. As a complete shift in sign of change, from positive to negative or the other way around, was observed in only 1–12% of the crop-region combinations under each scenario, the EcoCrop analysis can be considered to be robust.

3.3. Relationship between research intensity and nutrient output

In Fig. 3 we show the relationship between crop nutritional output and the number of publications for each crop in that region under future climate conditions. The results demonstrate the considerable research investments for certain starch crops, shown by the cloud grouping of crops in the upper right. These overinvestments occur

Table 3
Sensitivity analysis results. Crop-region suitability changes observed under the conditions of each of the sensitivity test. Values in brackets represent percentage values.

	No Change		Increase to Decrease		Decrease to Increase		Neutral to Increase or Decrease		Increase or Decrease to Neutral	
	Starch	Pulse	Starch	Pulse	Starch	Pulse	Starch	Pulse	Starch	Pulse
Tmin + 2C + 1 m	633	304	8	5	46	19	9	2	35	14
	(87)	(88)	(1)	(1)	(6)	(6)	(1)	(1)	(5)	(4)
Tmin-2C + 1 m	659	314	30	14	14	5	19	5	9	6
	(90)	(91)	(4)	(4)	(2)	(1)	(3)	(1)	(1)	(2)
Tmax + 2C + 1 m	634	307	7	3	55	23	14	3	21	8
	(87)	(89)	(1)	(1)	(8)	(7)	(2)	(1)	(3)	(2)
Tmax-2C + 1 m	635	300	38	26	22	4	14	3	22	11
	(87)	(87)	(5)	(8)	(3)	(1)	(2)	(1)	(3)	(3)
Pre + 25% + 1 m	642	312	15	6	24	8	8	2	42	16
	(88)	(91)	(2)	(2)	(3)	(2)	(1)	(1)	(6)	(5)
Pre-25% + 1 m	617	289	27	17	30	19	33	10	24	9
	(84)	(84)	(4)	(5)	(4)	(6)	(5)	(3)	(3)	(3)
Tmin + 2C − 1 m	661	294	11	7	25	25	13	8	21	10
	(90)	(85)	(2)	(2)	(3)	(7)	(2)	(2)	(3)	(3)
Tmin-2C − 1 m	633	289	31	13	17	16	35	10	15	16
	(87)	(84)	(4)	(4)	(2)	(5)	(5)	(3)	(2)	(5)
Tmax + 2C − 1 m	640	297	16	5	43	26	20	9	12	7
	(88)	(86)	(2)	(1)	(6)	(8)	(3)	(3)	(2)	(2)
Tmax-2C − 1 m	649	298	40	19	12	10	20	9	10	8
	(89)	(87)	(5)	(6)	(2)	(3)	(3)	(3)	(1)	(2)
Pre + 25% − 1 m	620	281	21	12	46	32	15	5	29	14
	(85)	(82)	(3)	(3)	(6)	(9)	(2)	(1)	(4)	(4)
Pre-25% − 1 m	647	300	30	17	15	9	31	14	8	4
	(89)	(87)	(4)	(5)	(2)	(3)	(4)	(4)	(1)	(1)
+ 1 m	662	315	10	9	24	7	14	3	21	13
	(91)	(92)	(1)	(3)	(3)	(2)	(2)	(1)	(3)	(3)
− 1 m	660	304	20	8	17	15	19	9	15	8
	(90)	(88)	(3)	(2)	(2)	(4)	(3)	(3)	(2)	(2)

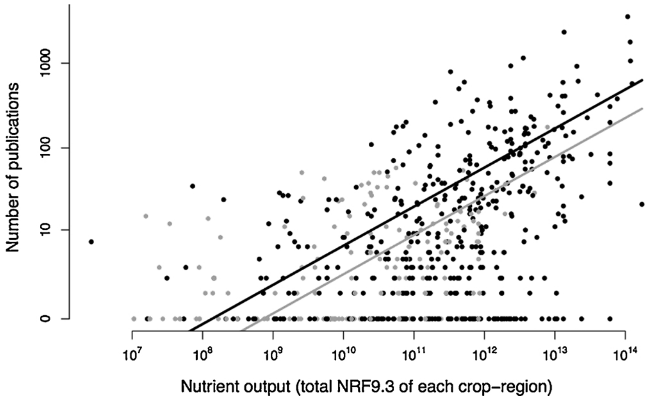


Fig. 3. Relation between the regional nutritional output and regional number of publications for each crop (both shown on a log scale). Black dots and the black regression line represent starch crops, the grey line and dots are pulses. The two regression lines have the same slope and only vary in their intersect.

across multiple regions for staple crops including rice and maize showing a disparity in research investments across crops. The "stripes" in the lower part of the graph are an artefact of the log-transformation on discrete small numbers (0, 1, 2, and 3 publications). The excessive number of values of 1 (representing 0 publications) represent regions that do not show publications for a particular crop, even though it is widely grown. Publications may show this pattern because the publication level for a certain crop in a certain region may often drop to zero in the absence of a specific research programme, rather than show a more gradual difference. This pattern in data is why we used a *zero-inflated* Poisson model, which takes into account this excess in zeros. We found that among different variables the energy output of each crop explains the zero inflation: lower energy output is associated with a higher probability of being zero. Other variables, including region, nutrient output, and monetary value of production did not explain the zero inflation. The lines in the graph indicate the values predicted by the Poisson model for starch crops (black line) and pulses (grey line), respectively.

3.4. Determinants of crop-specific agricultural research intensity

To assess how our choice to determine crop-specific agricultural research deficits by using nutritional output compares to using other criteria, we ran a zero-inflated Poisson model with more variables (Table 4). We scaled the variables to have a mean of zero and a standard deviation of 1, so that the size of each parameter reflects its relative importance in explaining the number of publications for each crop in each region, facilitating interpretation. The zero-inflation part of the model shows that when energy output goes up, the probability of having zero publications goes down. The results of the main model show that the total energy output of crops in each region is the most important variable explaining research intensity. Monetary value and energy output are highly correlated and monetary value provides only a small additional contribution. Nutrient output, however, has a substantial negative coefficient. This means that under equal conditions (same energy output, same region, etc.), a crop with higher nutrient output will receive less attention in scientific publications. Even though nutrient output itself is positively correlated with research intensity (see above, Section 3.3 and Fig. 3), this correlation seems to be due purely to the correlation between nutrient and energy output. In itself, the strong focus on energy in current research investments works against research on nutrient-dense crops. On top of the nutritional bias, there is also a bias against pulses, favouring starch crops. This clearly means that adopting nutrient output as the main congruence criterion indeed presents a major shift in crop-specific agricultural research priorities. It is also important to see that, *ceteris paribus*, crops that are expected to see a contraction in their suitable area under future climates currently have a slight, but statistically significant, higher research intensity than crops that are expected to see an expansion or remain stable. This is a small bias, but may indicate an overall vulnerability in how investments are made. There may be good reasons to keep investing in crops that are expected to decrease in climate suitability, but increasingly these investments would need to be directed to climate adaptation efforts, even to maintain current levels of crop productivity. It should be considered if these investments could not have higher returns when channelled to research on crops that will do better under future climates, increasing their productivity or improving processing and value addition.

Table 4
Zero-inflated Poisson model explaining the level of publications per region-crop combination. The regional contributions are omitted for reasons of space, but were also highly significant. Variables marked with an asterisk (*) were log-transformed and scaled to have a mean of zero and standard deviation of one, to facilitate comparisons.

Variable – *main model*	Coefficient	Standard error	z value	p value
Intercept	1.17	0.16	−7.11	< < 0.001
Energy output*	3.68	0.04	95.68	< < 0.001
Monetary value of crop production*	0.12	0.04	3.07	0.021
Positive change or stable in future climate suitability	−0.09	0.02	−5.72	< < 0.001
Crop group (pulses)	−0.84	0.03	−28.33	< < 0.001
Nutrient output*	−2.29	0.04	−57.25	< < 0.001
Variable – *zero-inflation model****8*				
Energy output*	−0.15	0.05	−2.65	0.008

3.5. Benchmarking

In Table 5A and 5B, we present the results for the benchmarking of starch and pulse crops. For each crop we show regional and global research deficits and excesses, along with the value of the Nutrient Rich Food index (NRF9.3) per 50 g of product. For comparative purposes, three different benchmarked results are presented: (1) results from all regions, (2) research deficit and excess in regions where the suitability of respective crops is expected to be positively impacted by climate change, and (3) research deficit and excess where respective crops are expected to be negatively impacted by climate change. The numbers under (2) and (3) add up to a number that is equal to (1), or lower than (1) when there are regions where climate models did not agree on the direction of the change in suitability. The crops are shown in alphabetical order. Fig. 4 presents the same data in a different format, making it possible to see how excesses and deficits are spread across regions. The last row of Fig. 4 is also informative in showing how total research intensity is spread across regions. This represents the distance of each region's intercept, from the regional regression, relative to the average intercept for all regions. This output is displayed as a quartile above or below this average. Results highlight the high research investments for Europe, whilst the contrary is true for regions of Asia, the Americas, and Africa.

3.5.1. Starch crops

Sweetpotato, potato, and wheat have the largest overall research deficits compared to the nutrients they are currently contributing to the food system. These deficits are spread across the globe in both developed and developing regions. Sweetpotato was found to have no excess of research in any of the regions and has the largest deficits in regions where its suitability is likely to increase. Its high nutritional value is behind this pattern. As an underresearched potential climate winner, sweetpotato seems an important candidate for additional investment. In

Table 5A
Current research deficits and excesses for starch crops (in number of publications).

Crop	NRF9.3 (per 50 g)	All regions				Regions where crop increases in suitability				Regions where crop decreases in suitability			
		Regional		Global		Regional		Global		Regional		Global	
		Deficit	Excess	Deficit	Excess	Deficit	Excess	Deficit	Excess	Deficit	Excess	Deficit	Excess
Banana	24	546	27	1096	52	512	17	941	51	30	6	126	0
Barley	63	60	1421	362	1711	15	860	131	1022	44	490	206	688
Buckwheat	74	249	38	269	83	247	12	235	83	3	0	4	0
Cassava	30	297	73	1366	41	154	57	863	0	72	67	400	41
Maize	24	24	4963	685	4798	2	4242	414	4059	22	898	234	739
Millet	52	306	20	670	30	298	20	571	30	8	0	99	0
Oats	80	649	19	792	42	339	19	402	0	308	19	345	42
Plantain	46	244	0	904	0	211	0	771	0	33	0	133	0
Potato	34	2450	198	3325	568	679	168	1303	403	1761	54	1962	164
Quinoa	72	0	14	4	0	0	14	0	0	0	14	4	0
Rice	36	188	4786	1329	5895	55	279	615	5437	22	151	253	176
Rye	71	771	0	631	33	503	0	339	25	262	0	174	8
Sorghum	59	252	146	815	80	201	74	380	70	48	29	375	0
Sweetpotato	161	3416	0	3315	0	2865	0	1957	0	515	0	1259	0
Taro	34	374	0	325	0	325	0	177	0	50	0	148	0
Wheat	69	1291	649	4834	2882	622	223	2780	842	668	622	2027	2039
Yam	42	198	3	430	10	183	0	363	5	13	0	66	0

contrast, for potato and wheat the situation is more complicated. Potato and wheat were found to have both research excesses across distinct regions, although in comparatively far smaller levels compared to their deficits. Potato has research deficits mainly in regions where the crop will likely experience less suitable climate conditions. For wheat, the deficits are distributed across regions with negative and positive climate effects. Regions in Asia, including China and India, show high research excesses for wheat and likely decreased suitability for the crop.

Only maize, rice, and barley have a net research excess both regionally and globally. In the case of maize, regions with excessive research are spread across the globe. In the case of rice, regions with research excess are concentrated in Asia, where rice is likely to increase in suitability under climate change. A concentrated investment in only three crops is driving the mismatch with nutrient output. A more diversified way of allocating research funds will be crucial to ensure future food and nutrition security. Fortunately, maize, rice, and barley are not especially vulnerable to decreasing climate suitability globally, although in certain regions, this may be an additional reason to consider reallocating research investments.

Rye, oats, millet, sorghum, and buckwheat were found to be important potential climate winners among the cereals. All have regional research deficits. These are generally hardy crops grown in stress-prone environments. Millet, a group of several species, is grown in very diverse environments and has research deficits on all continents, apart from the Americas. Millet species tend to be drought and heat tolerant. For millet, the regional research deficit is almost half that of the global deficit. Oat and buckwheat mainly occur in cold-stressed environments in temperate regions with higher R&D investments compared to millet and have similar regional and global deficits. Sorghum is underresearched globally rather than regionally, as it is primarily grown in poorer regions in the tropics.

Banana, a crop largely produced in tropical regions, was identified to have research deficits in sub-tropical and temperate regions across all continents, which may explain the observation of its global deficit being almost double that of its regional deficit. Plantain, cassava, yam, and taro similarly have global deficits larger than their regional research deficits. Regions of research deficit are tightly concentrated in tropical regions, where these crops are grown. Tropical regions receive less research investment than the global average. Sweetpotato, plantain, and taro are not overresearched in any region. The research deficits of banana, plantain, cassava, and yam are all concentrated in areas with projected increases of climate suitability of these crops. This makes the crops in this group important candidates for increased research investments.

3.5.2. Pulses

Indices of research deficits and excesses show that common bean, lentil, chickpea, and broad bean to be the most research deficient crops using both global and regional benchmarks. In regions where climate changed was modelled to potentially have positive impacts, lentil and broad bean were the most underresearched pulses. Lentil was found to have research deficits across all continents, spanning regions with both high and low R&D investments. Broad bean was identified with research deficits across temperate regions.

Cowpea and lupin under these conditions were both overresearched, with respect to their nutritional output. These crops were

Table 5B
Regional and global research deficits and excesses for pulses (in number of publications).

Crop	NRF9.3 (per 50 g)	All regions				Regions where crop increases in suitability				Regions where crop decreases in suitability			
		Regional		Global		Regional		Global		Regional		Global	
		Deficit	Excess	Deficit	Excess	Deficit	Excess	Deficit	Excess	Deficit	Excess	Deficit	Excess
Broad bean	46	344	0	87	20	260	0	40	16	83	0	47	4
Chickpea	83	199	124	145	295	164	55	92	166	35	32	45	129
C´mon bean	36	772	38	413	129	163	38	76	57	596	27	333	73
Cowpea	113	49	112	70	115	32	84	42	79	17	34	28	36
Lentil	86	375	27	205	59	277	17	129	43	98	0	76	16
Lupin	135	21	60	11	171	4	37	0	67	17	37	11	104
Pigeonpea	115	148	4	127	0	114	4	78	0	35	4	48	0

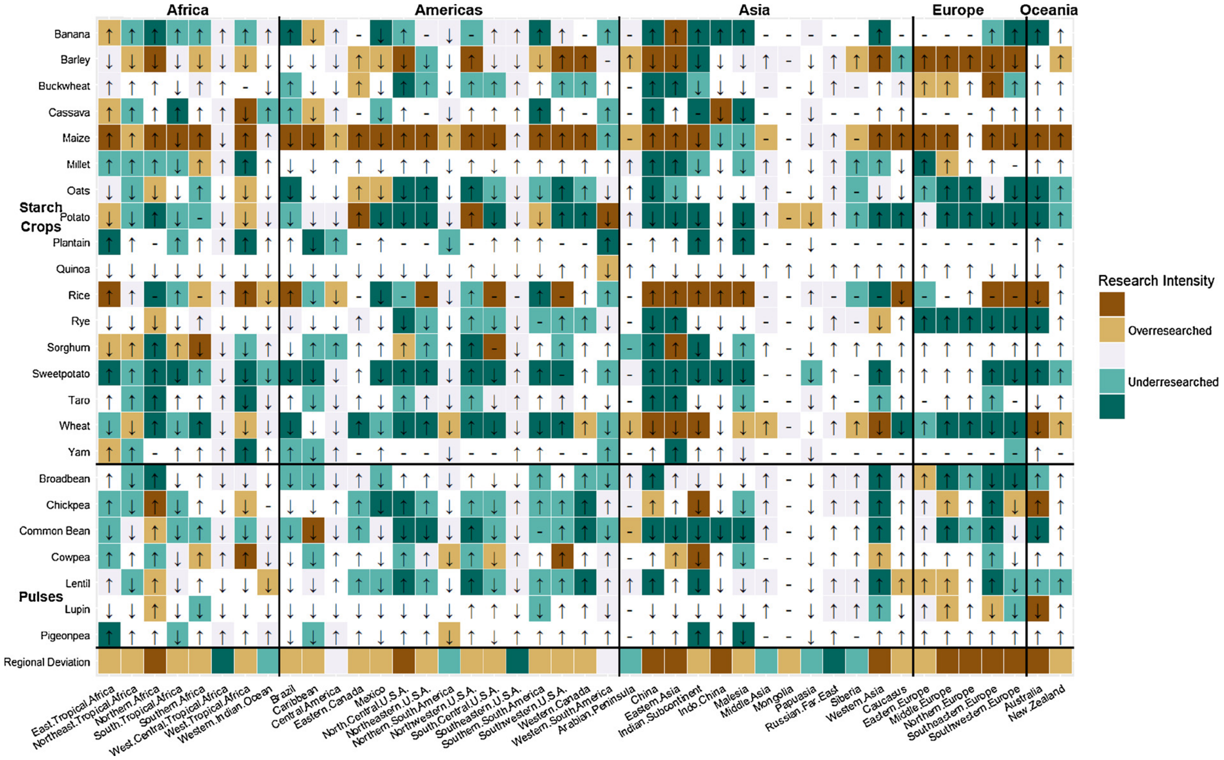


Fig. 4. Research intensity and climate impact for all crops and regions. Research intensity is categorised in quartiles above and below regional regression line. White represents crop-regions without data. Symbols show crop-region combinations that will benefit (↓), suffer (↑), or see no major change (-) due to climate change.

found to have far larger regional research deficits than global deficits. Chickpea research shows regional deficits, while from a global perspective the crop is net overresearched. This paradox means that research is concentrated in areas where the crop is not a major food crop for national consumption.

Pigeonpea and common bean were found to have regional deficits and global deficits, with their regional deficits higher than their global. The deficits for pigeon pea are located in tropical regions. Deficits for common bean are located in more temperate regions with higher R&D investments. It is strongly underresearched in large parts of Asia, but in these same areas, the crop is also projected to decrease in suitability. Cowpea was found to have an almost identical global and regional research deficit.

3.6. Regional patterns

Fig. 5 maps the geographical distribution of regional research deficits where crops were positively impacted by climate change. The research deficits for starch crops are, in general, heterogeneous, with both developed and developing regions displaying research deficiencies (Fig. 5a). In almost all regions, at least one crop was found to have a research deficit. We also identified regional clusters of research deficiency; the northwest of North America, northern and southern Africa, western South America, central Asia and China.

In contrast, pulses (Fig. 5b) showed far fewer regions with research deficiencies, but in those regions where deficiencies were identified, the proportion of crops with deficiencies was far higher. South Eastern Europe, the Caucuses, western Asia, and east tropical Africa were particularly deficient. Whilst almost the entirety of North America was found to be research deficient in at least 25% of analysed pulses.

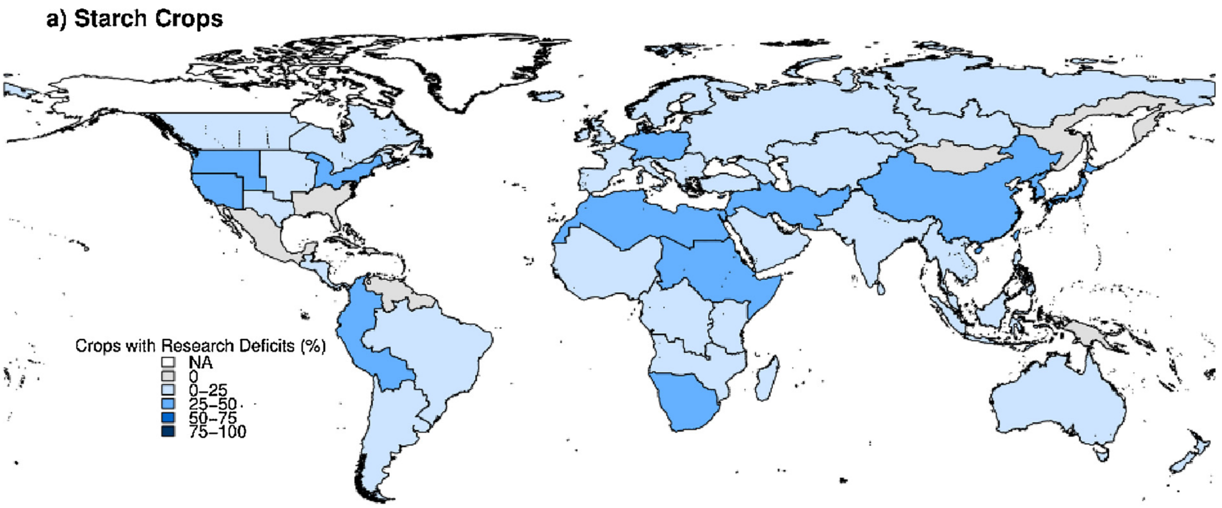
4. Discussion

4.1. Comparisons with other studies

Other studies have shown scenarios with similar impacts of climate change on the major crops. Rosenzweig et al. (2014) modelled that higher latitudes would see increases in wheat, maize, and rice yields; mid-latitudes increases in rice; with lower latitudes seeing general declines in crop yields. These results are generally mirrored in our suitability results. These results underline the importance of research identifying the factors that make the major crops susceptible to climatic changes (e.g. Jagadish et al., 2014; Reynolds et al., 2015).

Identified potential climate winner cereals including rye and millet showed great potential for cultivation under the modelled climatic changes, in many cases in regions where other cereals were found to be inhibited by climate change. At the same time, these crop species have large regional and global research deficits. Other modelling exercises gave similar results, showing the climate adaptation potential of these crops (Lobell et al., 2011; Challinor et al., 2014). A study in semi-arid eastern Zimbabwe, however, found that maize frequently out yields millets and sorghum, concluding that combining maize with millets and/or sorghum will be more realistic than a total replacement of maize (Rurinda et al., 2014). This same study also argues that substantial investments are needed to make millet more attractive to farmers, including the creation of better marketing channels for this crop, but that improved maize storage also deserves attention. It is important to point out that the results of our study only give an indication of the *relative* R&D effort suggested by the current contribution of crops to human nutrition and the degree to which climate change challenges future production. The results should not be interpreted as suggesting that R&D investment in certain crops, such as maize, should necessarily decrease in absolute terms.

Sweetpotato, a nutrient-rich crop, is modelled to expand on all continents, yet currently has extremely high regional and global research deficits. Naylor et al. (2004) highlight the benefits of investment



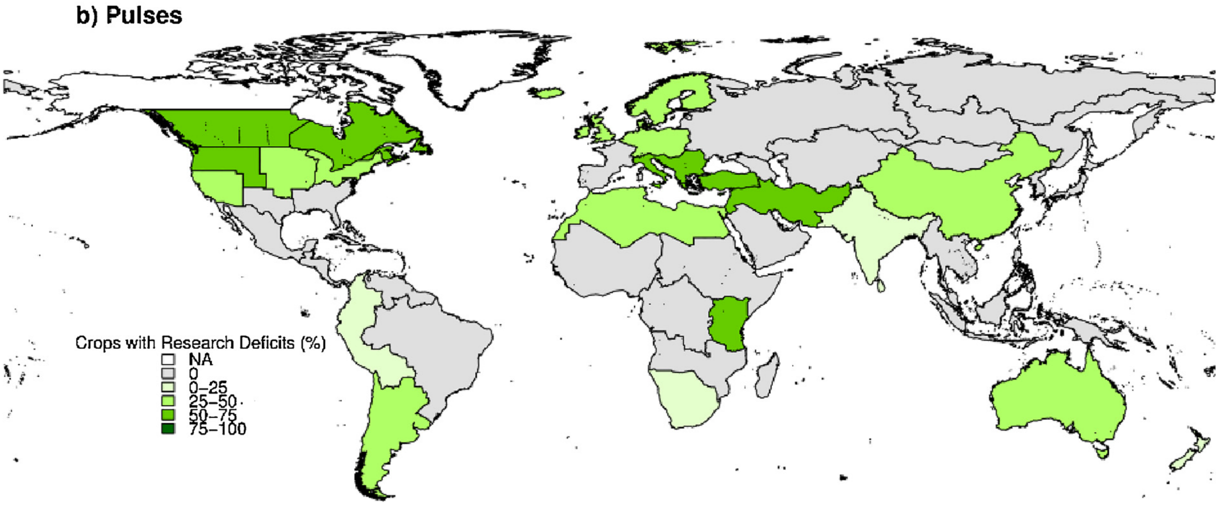


Fig. 5. Proportion of starch crops and pulses in each region with a research deficit under regional benchmarking.

in research of orphan crops like sweetpotato and millets, findings apparently gone unheeded. These results also demonstrate that such reallocation should be global, with research deficits found in both developed and developing countries, with pulses found to be especially research deficient in developed regions.

In an analysis similar to our own study (using the EcoCrop model), Jarvis et al. (2012) found that cassava will largely benefit from climate change, demonstrating the potential of cassava in climate change adaptation of African agriculture, and claiming the crop will play an important role. Our results put this call for attention for cassava in perspective. Our results confirm the potential of cassava under future climates. Other tropical crops like sweetpotato, millet, plantains, bananas, yam, and taro, however, each have a larger research deficit than cassava. Even though cassava is undeniably an important focus for continued R&D investments in Africa, it already receives substantial research attention. Other crops that can facilitate climate change adaptation are relatively more underresearched. Our analysis demonstrates that a broad perspective is needed to make objective R&D investment decisions. Current modelling exercises that narrowly focus on a handful of crops for which sophisticated crop growth models are available or that focus on crops that are covered by institutional mandates should be compared with analyses that take an inclusive, comparative perspective.

Pingali (2015) argues that the priorities of agricultural research investors are incongruent to nutritional requirements. Our analysis confirms quantitatively that an increased focus on nutrient output would effectively need a change in research intensity across crops. However, the development of crop-neutral investments, suggested by Pingali (2015), is unlikely to be sufficient to shift the allocation of investments. R&D capacity needs foresight-based public investment for future food and nutrition security. Global future public health benefits do not translate automatically in short-term business gains. For one thing, the climate signal does not translate into immediate business opportunities, even though transformational change is needed for climate adaptation. In addition, we suggest that the focus should not only shift from staple crops to more nutrient-dense fruits and vegetables, as suggested by Pingali (2015), but it should also begin to shift within staple crops. Emphasis could be increasingly moved towards potential adaptive cereals such as millet, oats or rye, and more nutrient-dense, adaptive staples such as sweetpotato, moving away from less adaptive, less nutritive crops in certain regions.

4.2. Other factors important for prioritisation

The present study has generated a number of insights that should influence the allocation of research investment with an improved focus on climate change and human nutrition. However, other factors also play an important role. Prioritisation should consider that changes in the agronomic and social importance of crops will not be driven or constrained by climate alone. Other drivers of change include growing populations leading agricultural intensification and technological change (Boserup, 1965), dietary shifts associated with growing affluence (Delgado, 2003; Kearney, 2010; Vranken et al., 2014), agronomic factors including yields (Stoddard, 2013), and alternative crop preference (von Richthofen et al., 2006). These drivers will also contribute to shifts in the importance of crop production. Voison et al. (2014) highlight the nexus between agronomic and social factors by suggesting that farm intensification and abandonment of traditional farming systems may also contribute to shifts in crop importance. Education and information distribution may also limit novel or underutilised crop production (Schneider, 2002; Manners, 2018, forthcoming).

The allocation of agricultural investments should account for these points and consider the role of transformative changes. R&D investments may assist in driving dietary changes, through development of palatable novel products using potential climate winner crops. It is imperative that investments are made not only to investigate the adaptive capacity of potential winner crops, but also the socio-economic capacity to produce, process, and consume them. The benefits of sweetpotato-based products, or those developed from other highly nutritious crops like lentil, broad bean or chickpea would be lost if crops rot in fields or processed products remain on shelves due to unresponsive supply chains or a lack of demand. Magrini et al. (2016) identified the need for encouragement of downstream industries to drive demand for underutilised crops. This reinforces the importance of value chains to steer the demand for crops and products that are both climatically and socially adaptive. The shift in R&D to underresearched crops may need to be accompanied by a shift in emphasis on R&D from production to processing, marketing and education, and consumption. These examples suggest the complexity behind shifts in the relative importance of crops across regions, even without the added effects of climate change. Therefore, any distribution in research efforts should not only consider the climatic potential of a crop, but also its socio-economic potential.

Eventually, different factors of influence should be considered jointly with climate change, for instance through scenario analysis (Vervoort et al., 2010). Multi-stakeholder prioritisation exercises, such as those promoted by Campbell et al. (2016), would need to interpret our results together with other results in consultations with a wide range of stakeholders to arrive at more solid conclusions. This will require a more interactive approach to our research results than what we can offer in this paper. Therefore, we offer our tables, scripts, and results as supplementary information to this article to allow more comprehensive exercises on crop research prioritisation under climate change (Available here: https://doi.org/10.7910/DVN/WDMSOL).

5. Conclusions

This study has highlighted the potential global impacts of climate change on an array of starch and pulse crops. Combining these results with information on the research dedicated to these crops we have been able to identify nutrient-rich crops that show adaptation potential to climate change and that should become high priorities for future investigation. In particular, sweetpotato, wheat, broad bean, and lentil were identified as climate change potential winner crops showing potential for cultivation under climatic changes, yet were found to have considerable research deficits in regions where they were found to increase.

Therefore, it is prudent for further consideration to be made of these underresearched crops, investigating their potential for climate change adaptation, ensuring nutrient security, and the potential for reallocating funds away from nutrient-poor crops that are likely to be affected by climate change. A number of these climate potential winner crops were found to see gains across multiple continents and across latitudes, reinforcing their diverse potential, and demonstrating that these crops are underresearched on many occasions at global and regional scales.

We hope that this study sparks a more rigorous debate on improved targeting of funding allocation of nutrient-rich crop adaptation to climate change and that it will encourage future studies that expand and refine our results. Future studies should also cover fruits and vegetables as well as neglected and underutilised crops, in order to fully consider the full range of crop R&D investment options for future food and nutrition security under climate change.

Acknowledgments

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Appendix A

Ecocrop Model Computation

As part of the Ecocrop model calculation 9 crop-specific parameters are used, which offer information about the environmental adaptation of a particular crop. These parameters include:

Kill minimum temperature (CropKillMinTemp)
Minimum temperature (CropMinTemp)
Minimum temperature for optimal range (CropMinTempOpt)
Maximum temperature for optimal range (CropMaxTempOpt)
Maximum temperature (CropMaxTemp)
Minimum precipitation (CropMinPrec)
Minimum precipitation for optimal range (CropMinPrecOpt)
Maximum precipitation for optimal range (CropMaxPrecOpt)
Maximum precipitation (CropMaxPrec)
Length of crop cycle (CropCycle)

These parameters were derived from the EcoCrop database, which holds 2568 plant species (FAO, 2012). For all parameters except one we used EcoCrop data directly. For the length of the crop cycle, the EcoCrop database gives a minimum and maximum value. We took the geometric mean of the two values to get the CropCycle value. The arithmetic mean often gave unreasonably long crop cycles in the case of annual crops, which will tend to underestimate the adaptation potential of crops. The minimum crop cycle, on the other hand, was extremely short and hardly representative of typical crop cycle values. The geometric mean gives a value between the arithmetic mean and the minimum value. For sorghum, the geometric mean gave a crop cycle of 6.5 months, close to the 6 months which gave the best fit in a modelling exercise with EcoCrop by Ramirez-Villegas et al. (2013). For other crops, also reasonable values were obtained with the geometric mean.

The following monthly climate data is used to determine the suitability.

Monthly minimum temperature (MonthMinTemp)
Monthly mean temperature (MonthMeanTemp)
Monthly total precipitation (MonthTotalPrec)

The calculation of suitability is done in three steps.

Step 1. As a first step, a thermal suitability is calculated for each month, a value between 0 (unsuitable) and 1 (fully suitable). This is determined using the following rules, for each month.

- If the minimum temperature of the month is less than the kill minimum temperature + 4 degrees Celsius of the crop, temperature suitability is set to zero.
- If the mean temperature of the month is lower than the minimum temperature of the crop or higher than the maximum temperature of

the crop, temperature suitability is also zero.

- Between the minimum temperature of the crop and the minimum temperature of the optimal range of the crop, the suitability for each month *i* is determined according to the following formula:
- SuitabilityTemp$_i$ = (MonthMeanTemp − CropMinTemp) / (CropMinTempOpt - CropMinTemp)
- Likewise, if the mean temperature is higher than the minimum temperature, but not high enough to reach the minimum temperature of the optimal range, the suitability for each month *i* is determined according to the following formula:

SuitabilityTemp$_i$ = (CropMaxTemp - MonthMeanTemp$_i$) / (CropMaxTemp - CropMaxTempOpt)

Taking in turn each month *i* of the year as a possible start of the growing season, the model evaluates the months that fall within the crop cycle.

Step 2. Then the suitability of each month regarding the precipitation is generated. Again, this is a value between 0 and 1. The EcoCrop model evaluates the total accumulated rainfall during the length of the crop cycle. The model takes in turn every month as the start of the crop cycle, summing the rainfall over the consecutive period with length CropCycle, including one month before and after this period. For each of the 12 rainfall sums, it determines whether it falls in the permissible range or in the optimal range.

- If the accumulated rainfall for the evaluated period is lower than the minimum rainfall of the crop or higher than the maximum rainfall of the crop, rainfall suitability is also zero.
- Between the minimum rainfall of the crop and the minimum rainfall of the optimal range of the crop, the suitability is determined according to the following formula:
- SuitabilityPrec$_i$ = (MonthPrec$_i$ – CropMinPrec) / (CropMinPrecOpt – CropMinPrec)
- Likewise, if the accumulated rainfall is higher than the minimum rainfall, but not high enough to reach the minimum rainfall of the optimal range, the suitability for each month *i* is determined according to the following formula:

SuitabilityPrec$_i$ = (CropMaxPrec - MonthMeanPrec$_i$) / (CropMaxPrec - CropMaxPrecOpt)

Step 3. From steps 1 and 2, we have two series of 12 suitability values, for temperature and precipitation respectively. The two series of values are combined by taking the minimum of the SutiabilityTemp and SuitabilityPrec values, for the consecutive months until reaching CropCycle. This results in a series of 12 suitability values. These values correspond to the potential suitability of the cropping period following each month of the year. The EcoCrop model reports the highest suitability value as the overall suitability value, assuming that farmers plant at the best moment. This does not take into account multiple cropping cycles during a single year, but it does account for potential shifts in planting dates as an adaptation measure taken by farmers.

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