

Global mismatches between crop distributions and climate suitability

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20 **The selection of new crops and the migration of crop areas are two key strategies for**
21 **agriculture to cope with climate change and ensure food security in the coming years.**
22 **However, both rely on the assumption that climate is a major factor determining crop**
23 **distributions worldwide. Here, we show that the current global distributions of nine of**
24 **twelve major crops strongly diverge from their modelled climatic suitability for yields,**
25 **after controlling for technology, agricultural management and soil conditions.**
26 **Comparing the climatic niches of crops and their wild progenitors reveals that climate**
27 **suitability is higher outside the native climatic range for six of these nine crops while all**
28 **of them are farmed predominantly in their native ranges. These results show that**
29 **agricultural strategies coping with climate change will be unsuccessful unless they fully**
30 **consider the social, cultural, and ecological factors underpinning crop distributions.**

31 Ensuring food security while adapting to climate change, and preserving the environment, is a
32 central challenge for humanity^{1,2}. Many solutions have been proposed, including the migration
33 of crop areas^{3–5} and the cultivation of novel species and varieties⁶ to identify the most promising
34 species and regions for food production under different scenarios of climate change. Most
35 studies on agricultural adaptation to climate change consider that climate is a major factor
36 determining the growth and productivity of crops, and that crop distributions can be optimized
37 for climate by human societies. However, such proposals often do not account for multiple
38 agricultural management (e.g. irrigation), cultural (e.g. preferences for certain crops from
39 farmers and consumers⁷), socio-economic (e.g. agricultural policies, subsidies, markets, and
40 international trade^{8,9}) and other ecological (e.g. pest pressure¹⁰) factors, that jointly determine
41 the current biogeographic patterns of crops.
42 The extent to which non-climatic factors matter on a global level for climate adaptation in
43 agriculture can be assessed through identifying mismatches between current climate suitability

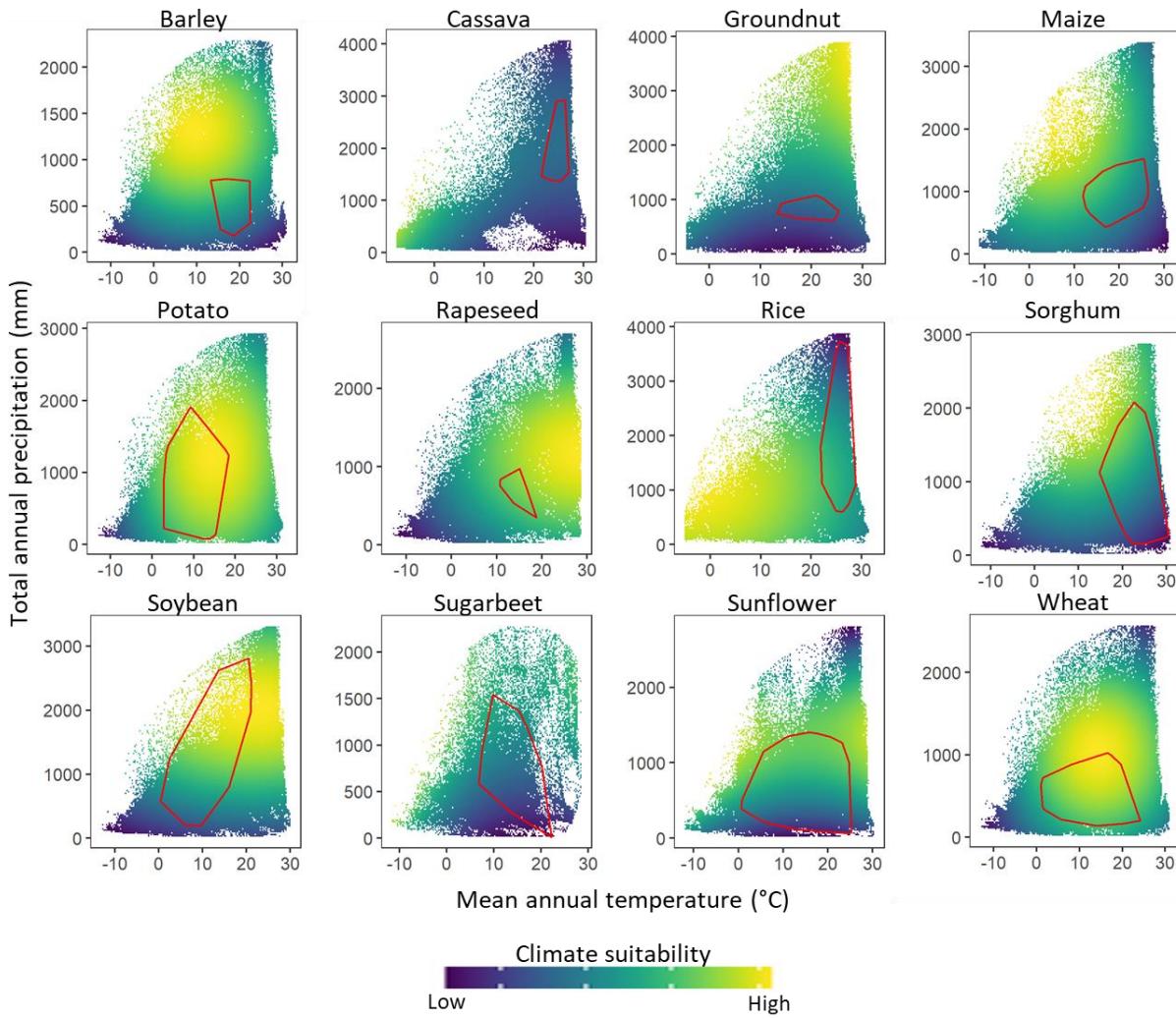
44 and crop distributions. Analysing crop distribution-climate suitability (mis)match is thus
45 critically important for any discussion on global climate adaptation in agriculture and more
46 generally, for understanding how humans and crops have co-evolved with climates.

47 Here we investigate the relationship between the global distributions of twelve major food
48 crops (Extended Data Table 1) and their climate suitability, using a global database of crop
49 distributions¹¹ and a crop-specific climatic niche model based on mean annual temperature
50 (MAT) and total annual precipitation (TAP). Both MAT and TAP are essential to the survival
51 and growth of domesticated and wild plant species and have recently been related to the global
52 distribution of croplands¹². Within the two-dimensional climatic space of each crop, we
53 assessed climate suitability by predicting the effects of MAT and TAP on crop yield while
54 controlling for agricultural inputs (i.e. irrigation and fertilization) and socio-economic factors
55 (i.e. gross net product and human development index) to account for differences in terms of
56 technological inputs, as well as numerous biophysical factors, including soil conditions and
57 topography (see Methods). We then tested for a significant correlation between climate
58 suitability and the fraction of cropland allocated to each crop (hereafter *crop area*), and mapped
59 the global distribution of the (mis)match between crop area and climate suitability (see
60 Methods). Further, we investigated the role of crop origins and agricultural expansion in the
61 relationship between the global distribution of crops and climate suitability. We used native
62 occurrences of the wild progenitors of each crop (Extended Data Table 1) to define their *native*
63 versus *expanded* climatic ranges (i.e. portion of the crop climatic space occupied by its wild
64 progenitors and by the crop only, respectively) and we compared crop area and climate
65 suitability between the two ranges.

66 The optimal climatic conditions for yield (Figure 1) and the distribution of cultivated areas
67 within crop climatic spaces (Figure 2) vary widely from one crop to another. Overall, our

68 analysis shows that the current global distributions of individual crops poorly match their
69 climatic potential. Among twelve major crops, the cultivation of only three - groundnut, maize
70 and soybean - predominates in climates that are predicted to be the most suitable for their yields
71 (blue in Figure 3). Conversely, cassava, rapeseed, rice and sunflower are mostly cultivated in
72 climates of low suitability for their yields (red in Figure 3). Moreover, the fraction of cropland
73 allocated to barley, potato, sorghum, sugarbeet and wheat is not significantly correlated with
74 their predicted climatic suitability (black in Figure 3). Adding the seasonality of temperature
75 and precipitation (i.e. two potentially important climatic factors for yields) to crops' climate
76 suitability models (see Methods) confirms that climate suitability is generally a poor predictor
77 of realized crop distributions (Extended Data Figure 1). The main differences with the
78 calculation of climate suitability based on MAT and TAP only are observed for wheat, whose
79 distribution of cultivated areas becomes negatively correlated with the suitability of climate,
80 and maize and soybean, whose area-suitability correlations become non-significant (Extended
81 Data Figure 1).

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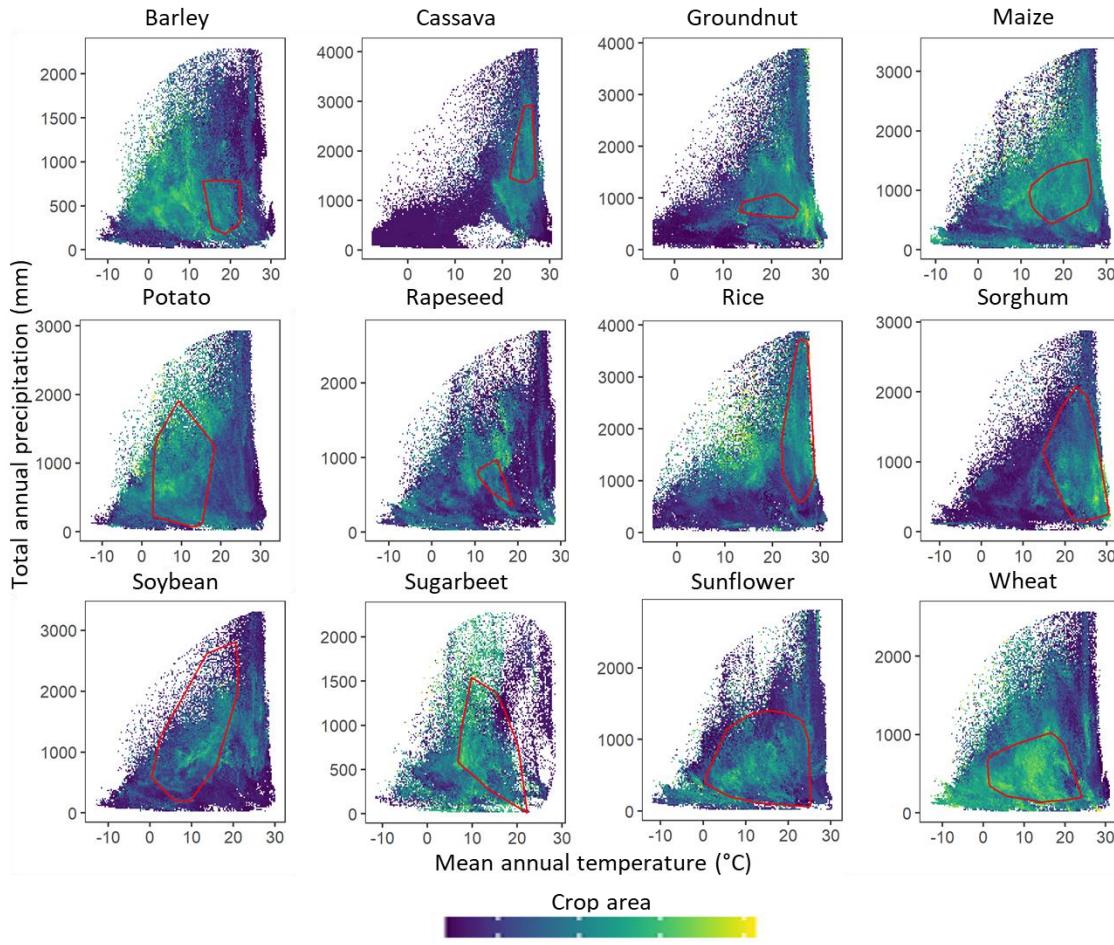
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84 **Figure 1: Climate suitability for the production of 12 major crops at the global scale.**

85 Climate suitability is predicted for each crop by modelling the effects of mean annual
86 temperature (MAT) and total annual precipitation (TAP) on yield while controlling for the
87 effects of various agricultural, socio-economical soil and topographic factors (see Methods).
88 Red polygons delineate the climatic space occupied by crop wild progenitors (i.e. native
89 climatic range).

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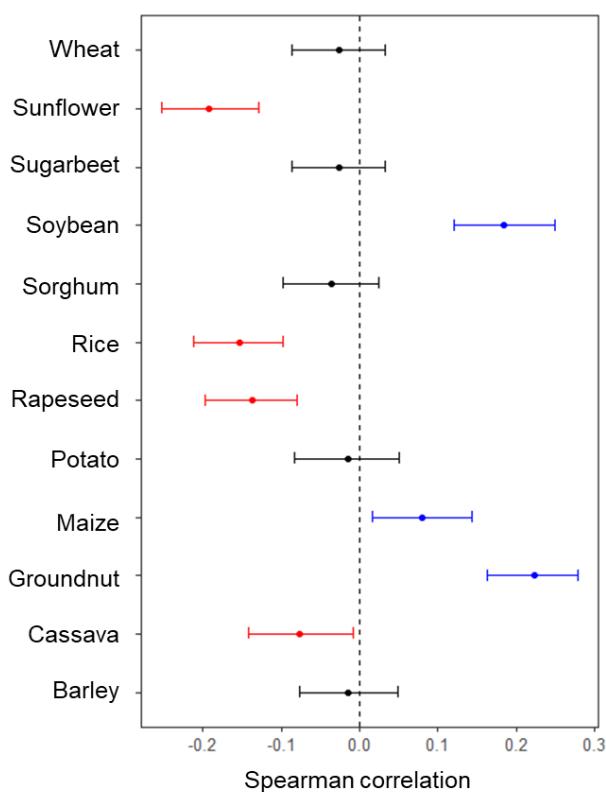
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93 **Figure 2: Distribution of the areas of 12 major crops within their two-dimensional**
94 **climatic space.** Crop area correspond to the fraction of total, available cropland devoted to
95 each crop. Red polygons delineate the climatic space occupied by crop wild progenitors.

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98 **Figure 3: Correlation between the fraction of available cropland devoted to each crop**
99 **and climate suitability.** Horizontal bars show confidence intervals ($\alpha = 0.05$) computed
100 from 1000 random resamplings (see Methods). The correlation is considered significant if the
101 confidence interval does not include 0. Black: non significant correlation; Blue: positive
102 correlation; Red: negative correlation.

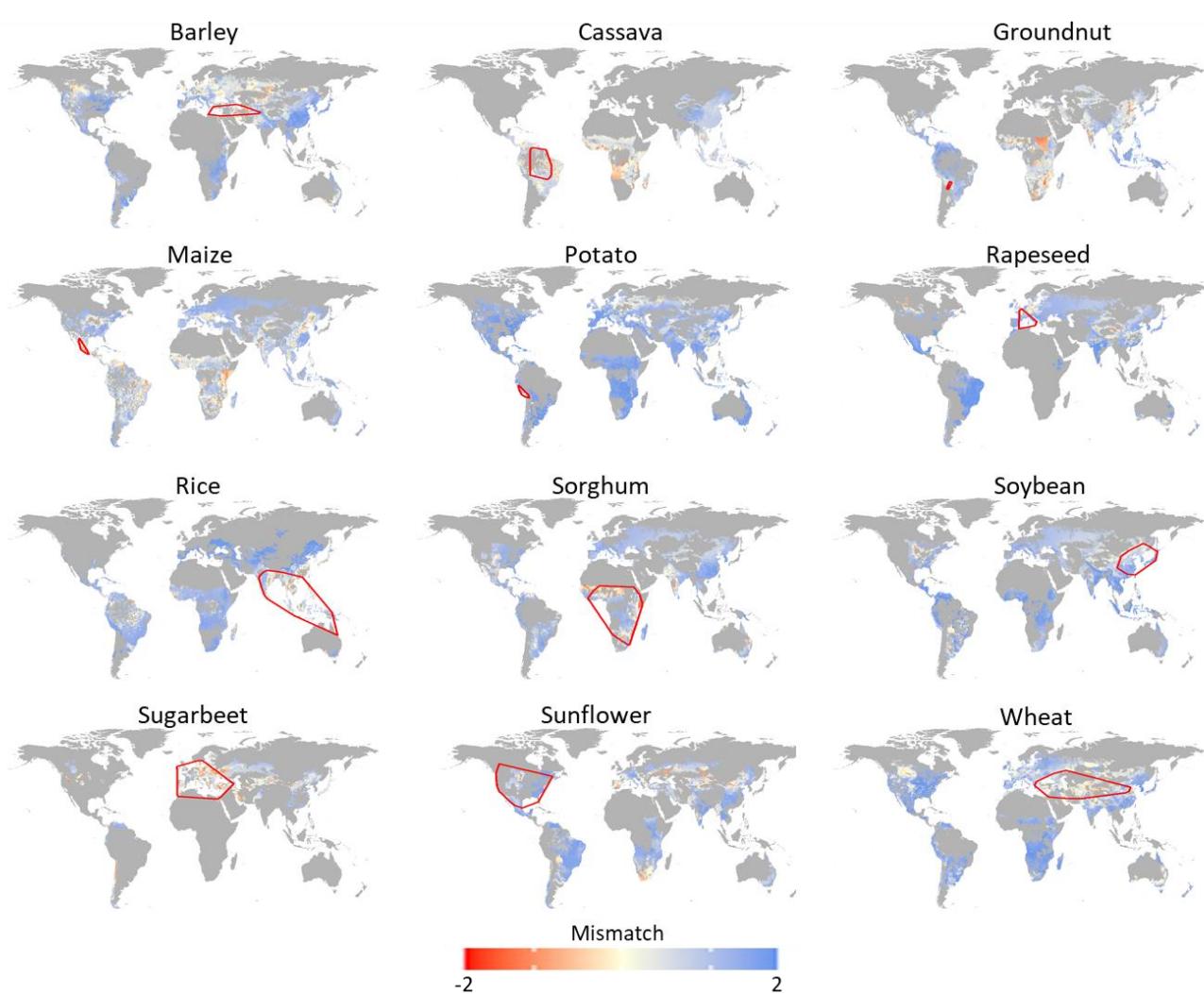
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104 The strong mismatch between modelled climatically suitable cropland areas and current
105 cultivation can indicate local limits to crop production, including climate, but can also allude
106 to the importance of many other ecological or socio-cultural drivers (Figure 4). Geographic
107 zones where the allocation of land to a crop is lower than predicted by its climatic suitability
108 represent 78-98% of the global crop area (positive mismatch scores; blue areas in Figure 4).
109 Different causes can explain such a dominant pattern, including the fact that some crops share
110 similar climatic optima (e.g. maize and sorghum; wheat and potato; rapeseed and soybean,
111 Figure 1), leading to competition for space. In addition, local food systems, and especially

112 smallholder ones, typically cultivate a diversity of crops to serve multiple purposes (livelihood,
113 subsistence, pest control^{13,14}). Similarly, management factors such as multiple cropping
114 systems¹⁵ and year-to-year crop rotations¹⁶ can create patterns of crop distributions that deviate
115 from the modelled climate optima for single crops. The presence of natural enemies (pests and
116 pathogens) may be another important explanation for the apparent mismatch between crop
117 distributions and their climate optima for yield. Indeed, crop pests tend to share the same
118 climatic niche as their host¹⁰ and thus farmers may choose to reduce the area allocated to a crop
119 that is too intensely exposed to pests. We test this hypothesis for sunflower, using occurrence
120 records of *Sclerotinia sclerotiorum* (adapted from Mehrabi et al. 2019¹²), a major sunflower
121 pathogenic fungus worldwide. We find that the mismatch between climate suitability and the
122 fraction of cropland allocated to sunflower is lower in pest free areas than in areas where the
123 pest occurs (Extended Data Figure 2), suggesting a strong ecological anchoring of the
124 mismatches between climate suitability and current cultivation areas.

125 Our findings also highlight regions where the fraction of cropland devoted to a crop is large
126 relative to the suitability of climate for its yield (2-21% negative mismatch scores; red areas in
127 Figure 4). This is particularly true in (1) Eastern Europe and Central Asia for barley, sugarbeet
128 and sunflower; (2) Central and Eastern Africa as well as South America for cassava and maize;
129 (3) Eastern and South Africa, South India and Eastern Asia for groundnut and (4) Western and
130 Eastern Africa for sorghum (Figure 4). Deeper insights into the social systems in which these
131 crops are grown may explain these patterns. For example, cassava is a key crop for food
132 security across the African continent. It represents a lifeline when other crops fail due to
133 droughts, pest outbreaks, especially during the hunger season¹⁷. Thus even if yields may be
134 comparatively low, they are reliable under marginal conditions¹⁷. Other factors not related to
135 yield or food security likely play out in other situations. For example, agricultural policies, and

136 market distortions such as fixed prices and subsidies, can help explain why maize is cultivated
137 to a wider spatial-climatic extent than its climate optimum might predict⁹.



138 **Figure 4: Mismatches between the fraction of available cropland devoted to each crop**
139 **and climate suitability for their yield.** Mismatch is computed as the log ratio of climate
140 suitability divided by the fraction of cropland each crop occupy (see Methods). Positive scores
141 (blue) are regions where crop areas are low relative to climate suitability. Negative values (red)
142 indicate regions where cultivated areas are large with respect to climate suitability. Yellow
143 designates regions where cultivated areas and climate suitability are in equilibrium. Red
144 polygons delineate the geographic space occupied by crop wild progenitors (i.e. native range).

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147 Major crops by definition have undergone substantial geographical expansion from their
148 respective regions of origin to the rest of the world¹⁸. They have adapted to new climates
149 through historical globalization, including trade and innovations in agricultural practices,
150 especially irrigation¹⁹. However, the resulting current distributions of crops in comparison to
151 the native distributions of their wild progenitors, with regard to climate suitability, remains
152 poorly quantified¹⁸. We find that the fraction of agricultural land allocated to a given crop is
153 higher in native than in expanded climatic ranges for all crops except barley and groundnut
154 (Figure 2 & Extended Data Figure 3). Since areas of early crop domestication likely occur in,
155 or nearby, the native distributions of their progenitors^{20,21}, our results reveal that major crops
156 are farmed predominantly in the same climates as their geographic origins, potentially
157 indicating the biological constraints of crop species to wide climate adaptation. Native climatic
158 ranges are also more associated with climatic suitability than expanded ones for cassava, maize,
159 potato, rapeseed, sorghum and wheat (Figure 1 & Extended Data Figure 3), suggesting that
160 these crops are still better adapted to the climates of their origins. Conversely, native climatic
161 ranges are less suitable for barley, groundnut, rice, soybean, sugarbeet and sunflower when
162 compared to climate suitability in crops' expanded ranges (Figure 1 & Extended Data Figure
163 3). These results corroborate suggestions that humans have introduced crops into climatically
164 more suitable areas outside their native ranges¹, although we cannot rule out the possibility that
165 climate might also have changed since domestication into less suitable conditions in native
166 ranges²². Perhaps most importantly, varietal selection, mutations, and plant breeding has
167 modified the ecological requirements of crops so that they have become much more widely
168 adapted²³.

169 The relationship between wild species distributions and performance (usually in some yield
170 equivalent, such as fitness) is a core issue in the ecological niche theory^{24,25}. Our investigation
171 of cultivated species shows that climate suitability is a poor predictor of the current distribution

172 of crops, even after controlling for agricultural management, technology proxies and soil
173 conditions. Building crop climatic niches has previously been proposed as an approach to
174 ensure global food security by guiding species selection⁶ and by identifying new potential areas
175 to cultivate^{5,26,27} under future climate scenarios. However, our work shows the importance of
176 other, non-climatic factors, in determining crop distributions today. The mismatches we found
177 between crop distribution and climate suitability could serve as a basis for further research to
178 better understand the determinants of the global distribution of crops, notably the role of
179 ecological factors such as the presence of pests and their predators, as well as key social factors,
180 such as nutrition, resilience and markets. In turn, greater insights into these multiple factors
181 could help to integrate the climatic requirements of crops into agricultural planning. Finally,
182 our study tells a remarkable story of how humans and crops have co-evolved with climates
183 over the course of agricultural history, well beyond climatic constraints generally considered
184 to be highly determinant of species distributions. Extending our approach to less studied
185 'orphan crops'^{28,29} which haven't been moved around as much as major crops and which are less
186 heavily managed will help to extend the insights provided here further.

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253

254 **Figure legends**

255 **Figure 1: Climate suitability for the production of 12 major crops at the global scale.**

256 Climate suitability is predicted for each crop by modelling the effects of mean annual
257 temperature (MAT) and total annual precipitation (TAP) on yield while controlling for the
258 effects of various agricultural, socio-economical soil and topographic factors (see Methods).

259 Red polygons delineate the climatic space occupied by crop wild progenitors (i.e. native
260 climatic range).

261 **Figure 2: Distribution of the areas of 12 major crops within their two-dimensional**
262 **climatic space.** Crop area correspond to the fraction of total, available cropland devoted to
263 each crop. Red polygons delineate the climatic space occupied by crop wild progenitors.

264 **Figure 3: Correlation between the fraction of available cropland devoted to each crop**
265 **and climate suitability.** Horizontal bars show confidence intervals ($\alpha = 0.05$) computed
266 from 1000 random resamplings (see Methods). The correlation is considered significant if the
267 confidence interval does not include 0. Black: non significant correlation; Blue: positive
268 correlation; Red: negative correlation.

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273 values (red) indicate regions where cultivated areas are large with respect to climate
274 suitability. Yellow designates regions where cultivated areas and climate suitability are in
275 equilibrium. Red polygons delineate the geographic space occupied by crop wild progenitors
276 (i.e. native range).

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278 **Materials and Methods**

279 *Agricultural data set*

280 We studied barley, cassava, groundnut, maize, potato, rapeseed, rice, sorghum, soybean,
281 sugarbeet, sunflower and wheat (Extended Data Table 1). The global distributions of harvested
282 areas and yields were extracted from public data sources¹¹ in the form of rasters of 5 arc-
283 minutes resolution (~10km). These 12 crops were chosen because (1) they are widely cultivated
284 worldwide and provided more than 70% of food globally; (2) data on the amount of fertilizers
285 – known as a major driver of crop yields globally - are available at a 5 arc-minutes resolution³⁰
286 and (3) their wild progenitors can be identified in the literature²⁰ and have at least 20 recorded
287 occurrences in the wild (Extended Data Table 1). We used the global distribution of cropland³¹
288 to compute the fraction of available cropland allocated to each crop at a 5 arc-minutes
289 resolution. Nutrient application on major crops and the percentage of land area equipped for
290 irrigation³² were downloaded as 5 arc-minutes rasters.

291 *Crop progenitors*

292 We identified 23 progenitors of the 12 crops using published literature²¹. Wheat includes
293 *Triticum aestivum* and *Triticum durum*, which are the two main wheat species farmed
294 worldwide. Therefore, we considered the progenitors of both wheat species. Rice also includes
295 two different species, *Oryza sativa* (Asian rice) and *Oryza glaberrima* (African rice). However,

296 because *O. sativa* is by far the principal cultivated rice species, we only considered the wild
297 progenitors of the Asian rice in our analysis. We extracted progenitor occurrence records from
298 five global and two regional databases. We used the *BIEN* and *rgbif* packages in R to download
299 global occurrence records from the Botanical Information and Ecology Network³³ and the
300 Global Biodiversity Information Facility³⁴ databases, respectively. In addition, we extracted
301 global occurrences of crop wild progenitors from “A global database for the distributions of
302 crop wild relatives”³⁵, the BioTIME database³⁶ and GENESYS³⁷. We downloaded further
303 regional occurrences using the RAINBIO database, which contains records for Sub-Saharan
304 African vascular plants³⁸ and *speciesLink*, a national database for plant and animal occurrences
305 in Brazil³⁹. Because occurrence data are often inaccurate⁴⁰, we removed records with no
306 coordinates and that were documented before 1950. We used the *CoordinateCleaner* package
307 in R⁴¹ to remove occurrence records found within a 1 km radius of country and capital
308 centroids, with equal longitude and latitude coordinates, or assigned to institutional locations
309 such as botanical gardens, herbaria or the GBIF Headquarters. We also removed records with
310 high coordinate uncertainty (over 10 km), cultivated records (e.g. breeding/research material,
311 advanced/ improved cultivar, GMO and those found in markets or shops, institutes/ research
312 stations and genebanks and from seed companies), and records located in the sea/oceans. For
313 progenitors with the same species name as their crop, we only extracted records confirmed as
314 wild and ignored any record with an unknown cultivation status. In addition, we removed
315 records outside of the species reported native range to ensure no introduced and cultivated
316 record was included. Native ranges were identified at administrative levels according to the
317 USDA Agricultural Research Service, Germplasm Resources Information Network⁴². We
318 removed duplicates by keeping only one record for each species per 20 km grid cell. After
319 discarding the less accurate occurrence records, 4064 unique occurrence points remained for
320 23 wild progenitor species of the 12 crops (Extended Data Table 1).

321 *Climate data*

322 We acquired mean annual temperature (MAT) and total annual precipitation (TAP) data at 30
323 arc-seconds (~1 km) for the years 1979–2013 from the CHELSA database⁴³. We also used
324 temperature and precipitation seasonality to account for their potential effects on crop yields.

325 *Soil, topographic and socio-economic data*

326 We integrated soil pH, soil organic content, soil water capacity, slope as well as the human
327 development index and gross net product, two proxies of technological inputs, to control for
328 their effects on crop yields. These layers are freely accessible at the URLs provided in Extended
329 Data Table 2.

330 *Climate suitability*

331 For each crop, we estimated climate suitability by modelling the effects of MAT and TAP as
332 second order polynomials on crop yield while controlling for the effects of fertilisation and
333 irrigation (as second order polynomials) as well as all other soil, topographic and socio-
334 economic factors. We upscaled all the agricultural (i.e. crop yields and areas), climatic, soil,
335 topographic and socio-economic layers to 10 arc minutes resolution (~20 km). We worked at
336 such a resolution because climate is expected to be the main driver of species distribution at
337 large scales, whereas other factors might become more important with lower grain size⁴⁴. In
338 doing so, we also minimized incorrect assignment of climatic variables to the occurrence
339 records for which precision is not always communicated by data sources. We used the
340 estimated coefficients of this model (Extended Data Table 3) to compute climate suitability as
341 the yields predicted only by MAT and TAP. Crop yields were square root-transformed to assure
342 linearity. We then tested the robustness of the climate suitability model on 1,000 data subsets,
343 each constructed by randomly sampling 1,000 points (without replacement and without

344 stratification) from the data set (pixels) of each crop. We identified covariates that have a
345 significant effect on crop yields using the confidence intervals (alpha = 0.05) of the estimates
346 from these random re-samplings. In addition, we used the sums of squares to quantify the
347 amount of global variability in crop yields explained by the different factors (Extended Data
348 Table 3). Finally, we repeated this procedure by adding temperature and precipitation
349 seasonality to the climate suitability model (Extended Data Table 4).

350 *Correlation between crop areas and climate suitability*

351 We calculated the Spearman correlation index between the fraction of available cropland
352 allocated to each crop and climate suitability to test whether the global distribution of crops
353 matches their climate suitability. Because sample sizes were extremely large (i.e. between 52
354 011 and 176 318 pixels; Extended Data Table 1), we randomly sampled 1000 pixels 1000 times
355 and computed the confidence interval of the Spearman correlation indices to test for their
356 significance (alpha = 0.05).

357 *Mismatch index*

358 To compare the spatial distribution of climate suitability (Extended data Figure 4) and crop
359 areas (Extended data Figure 5), we computed for each crop a mismatch index as the log-ratio
360 of climate suitability divided by the fraction of cropland covered by each crop in each 10 arc-
361 minutes pixel. We previously scaled both variables between 1 and 2 so that mismatch values
362 vary between -2 (climate suitability is low with respect to cropland proportion) and +2 (climate
363 suitability is high relative to cropland proportion; Figure 4).

364 *Native and expanded climatic ranges*

365 We defined a crop's native climatic range by drawing a convex polygon around the occurrence
366 points of the pool of its wild progenitors⁶ within the two-dimensional climatic space of each

367 crop. By contrast, crop expanded range refers to the part of this two-dimensional climatic space
368 that is not covered by the progenitors. Although several techniques can quantify species'
369 climatic range⁴⁵, convex hull methods appear to be particularly relevant for large-scale
370 agricultural applications and its relatively simple concept makes it easily interpretable⁶.
371 Because the use of convex polygons is sensitive to outliers, we removed occurrence points with
372 Mahalanobis distance values ≥ 10 from the wild progenitors' niche space defined by MAT and
373 TAP⁶. This threshold was selected based on visual inspection of the data.

374 *Difference in crop areas and climate suitability between current and native ranges*

375 To compare crop climate suitability and crop area between the native and the expanded crop
376 climatic ranges, we calculated the difference in mean climate suitability (and area) between
377 native and current ranges. To aid in comparison between crops, we further divided this
378 difference by the mean climate suitability (or cropland fraction) in the current niche. We tested
379 for statistical significance of these standardized differences by randomly resampling 450 pixels
380 of the native and current range 1000 times and calculated confidence of interval ($\alpha = 0.05$)
381 (Extended Data Figure 3). In doing so, we overcome the negative correlation between sample
382 size and value.

383 *Pest data*

384 We tested whether the presence of crop pests could explain the mismatches between crop area
385 and climate suitability. However, since this hypothesis was not the main research question of
386 this article, we restricted our analysis to the sunflower and its widespread pest *Sclerotinia*
387 *sclerotiorum*. We focused on these two species because they have recently been the subject of a
388 climatic niche study conducted at the global scale¹⁰, so that occurrence data of *S. sclerotiorum*
389 were directly available. To test our hypothesis, we compared the mean of the mismatch between
390 crop area and climate suitability (in absolute value) between pest-free and pest-presence areas.

391 All analysis were conducted using R version 4.0.3.

392 **Data availability**

393 The sources of all data used in this study are referenced in the Methods and all raw data are
394 freely accessible at the URLs provided in Extended Data Table 2. The dataset used for the
395 analyses is available from the corresponding author upon request (lucie.mahaut@cefe.cnrs.fr).

396 **Code availability**

397 The detailed script used for the analyses will be available online at the following URL: xxx

398 **Methods references**

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447 **Author contributions**

448 L.M. led the data analysis and writing. L.M., S.P., D.R. and C.V. designed the experiment.
449 F.B., C.K.K., R.M and C.P. contributed substantially to the crop wild progenitors' analysis and
450 writing. J.Y.B., S.P., D.R. and C.V. assisted with data analysis and writing. Z.M. and L.H.R.
451 assisted with study design and writing.

452 **Competing interests**

453 The authors declare no competing financial interests.

454 **Additional information**

455 Supplementary information, including Extended Data Tables and Extended Data Figures are
456 available online.

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460

461 **Extended Data Table Legends**

462 **Extended Data Table 1. List of crop and associated wild progenitors.** N gives the number
463 of occurrence (pixels) considered in the analysis.

464

465 **Extended Data Table 2. Source of data supporting findings**

466

467 **Extended Data Table 3. Outputs from the climate suitability models.**

468 MAT: mean annual temperature; TAP: total annual precipitation; %Var: Percentage of
469 explained variance by each predictor; r^2 : adjusted coefficient of determination. Grey values
470 show coefficients that are significant (see Methods)

471

472 **Extended Data Table 4: Outputs from the climate suitability models when accounting for
473 climate seasonality.** MAT: mean annual temperature; TAP: total annual precipitation; %Var:
474 Percentage of explained variance by each predictor; r^2 : adjusted coefficient. Grey values show
475 coefficients that are significant (see Methods)

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486 **Extended Data Figure Legends**

487

488 **Extended Data Figure 1: Correlation between the fraction of available cropland devoted**
489 **to each crop and climate suitability when accounting for temperature and precipitation**
490 **seasonality.** Horizontal bars show confidence intervals (alpha = 0.05) computed from a random
491 resampling procedure (see Methods). The correlation is considered significant if the confidence
492 interval does not include 0. Black: non significant correlation; Blue: positive correlation; Red:
493 negative correlation.

494

495 **Extended Data Figure 2: Mismatch difference between *Sclerotinia sclerotiorum* free areas**
496 and areas where the pest occurs. *S. sclerotiorum* is a main sunflower's pest worldwide. A
497 positive mismatch score indicates that a low fraction of cultivated area is allocated to the crop
498 while climate suitability is high. This mismatch is significantly lower in pixels with no pest (N
499 = 129126) than with pests (N=66) (Wilcoxon test, W = 3586862, p-val = 0.026). Center line,
500 median; box limits, upper and lower quartiles; whiskers, 1.5x interquartile range; points,
501 outliers.

502

503 **Extended Data Figure 3: Standardized differences in the fraction of cropland allocated to a**
504 **crop (a) and climate suitability its yield (b) between native and current climatic ranges.** Positive
505 values indicate higher mean in the native range while negative values correspond to higher
506 mean in the current range. Horizontal bars show confidence interval (alpha = 0.05) computed
507 from 1000 random resamplings (see Methods). The difference is considered significant if the
508 confidence interval does not include 0.

509

510 **Extended Data Figure 4:** Maps of climate suitability for crop production. Climate suitability
511 is predicted for each crop by modelling the effects of mean annual temperature (MAT) and
512 total annual precipitation (TAP) on crop yield (see Methods). Yellow colors represent zones of
513 high climate suitability for crop production. Dark blue show zones of low climate suitability
514 for crop production. Red polygons delineate the climate space occupies by crop wild
515 progenitors.

516

517 **Extended Data Figure 5:** Maps of the fraction of available cropland allocated to each crop.
518 Yellow colors represent zones where the crop covers large proportion of available cropland.
519 Dark blue show zones where the crop occupies low fraction of available cropland. Red
520 polygons delineate the climate space occupies by crop wild progenitors.

521