The impact of climate change on the productivity of conservation agriculture

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Article

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13

14   **Abstract**

15   **Conservation agriculture (CA) is being promoted as a set of management practices that can**
16   **sustain crop production while providing positive environmental externalities. However, its**
17   **impact on crop productivity is still hotly debated, and how this productivity will be affected by**
18   **climate change remains uncertain. Here we compared the productivity of CA vs. conventional**
19   **tillage (CT) systems under current and future climate conditions using a probabilistic machine-**
20   **learning approach at the global scale. We reveal large differences in the probability of yield gains**
21   **with CA across crop types, climate zones, and geographical regions. We show that, for most crops,**
22   **CA performed better in continental, arid and temperate regions than in tropical ones. Under**
23   **future climate conditions, the relative productive performance of CA is expected to increase for**
24   **maize in almost all cropping areas within the tropical band, thus improving the competitiveness**
25   **of CA for this major crop.**

26   Conservation agriculture is a crop production system based on three principles: minimum soil
27   disturbance (going as far as no tillage or NT), permanent soil cover with crop residue, and diversified
28   crop rotation[1]. In compliance with sustainability goals, CA is designed to ensure the long-term crop
29   production while improving crop resilience to climate change and protecting the environment. It has
30   been shown to enhance soil carbon sequestration, improve soil quality, reduce soil erosion, and increase
31   biodiversity[2,3]. However, since the productivity of crops depends on many interacting factors including
32   local climatic conditions[4], soil characteristics[5], and agricultural management practices[6], it is difficult to
33   assess the potential of CA to increase agricultural productivity. Based on recent meta-analyses [5–7]
34   synthesizing current evidence on the effect of CA on crop yields, CA is expected to lead to a yield
35   reduction[6] compared to CT. However, the heterogeneity of the experimental results on CA vs. CT is
36   very large, and their outcome varies as a function of climate conditions[6] and management practices[6–8].
37   Most of the above studies relied on a synthetic aridity index or a large climate zone to characterize the
38   impact of climate, which makes it hard to analyze the response of CA productivity to inter-annual
39   weather variability or to predict the impact of future changes in climate. To date, a comprehensive,
40   global synthesis of the impact of climate change on the productive performance of CA with respect to
41   CT systems is still lacking.

42 In this paper, we compared the crop yields of CA and CT systems under current and future climate
43 conditions based on a new, global database of paired yield observations of NT (including CA and NT
44 without crop rotation and/or residue retention) vs. CT. We compiled the datasets collected from the
45 previous meta-analyses [5–7], and supplemented them by the latest literature references on this topic and
46 the inclusion of a broader set of climatic variables from external databases, such as precipitation (P) [9],
47 minimum air temperature (Tmin) [10], average air temperature (Tave) [9], maximum air temperature (Tmax)
48 [10] and potential evapotranspiration (E) [11,12] over the crop growing seasons [13] considered in each
49 experiment. As an indicator of water availability for crops, the precipitation balance (PB) was defined
50 as (P – E) over the growing season[5].

51 A machine learning model based on random forest [14] was trained and cross-validated based on 4071
52 paired yield data of NT (including CA and NT without crop rotation and/or residue retention) vs. CT to
53 map the probability of yield gain from CA (NT with crop rotation and residue retention), i.e.
54 $\left(\frac{Yield_{CA}}{Yield_{CT}} > 1\right)$, at a spatial resolution of $0.5° \ latitude \times 0.5° \ longitude$ based on current (2011-2020)
55 and future (2051-2060) average climatic conditions for eight major crops (barley, cotton, maize, rice,
56 sorghum, soybean, sunflower, and wheat). Crop types, soil types and management practices were kept
57 unchanged in all climate scenarios. The maps were then used to calculate the accumulated fractions of
58 the cropping area as a function of the yield gain probability of CA vs. CT, and as a function of the level
59 of change on the probability of yield gain from CA vs. CT in future climatic condition. These fractions
60 show the proportions of cropping area with low to high probabilities of yield gain from CA vs. CT, and
61 with low to high change level on the probability of yield gain from CA vs. CT under climate change.
62 They were both computed at the global scale and in different climate zones[15]. The results were used to
63 identify the favorable and unfavorable climate zones for CA, and to assess the climate change impact
64 on the productivity of CA in different climate zones. The details of model setting for global projection
65 are explained in the **Methods** section and further detailed in S1.

66 Our results show that, under current climate condition, CA is associated with a high chance of yield
67 loss under tropical climates (Figure 1) and that, for most of the studied crops, the overall probability of
68 yield gain is higher in continental, arid, and temperate regions than in tropical regions (Figure 1a, Figure
69 1b, Figure 1d-g). The risk of yield loss with CA is particularly high for rice, with a probability of yield
70 gain with CA under 50% in about 80% of the global rice cropping area. This fraction rises to about 100%
71 in the tropics (Figure 1d).

72 For several crops and climate regions, the estimated effect of climate change on the probability of yield
73 gain with CA is relatively moderate. In approximately half of the cropping areas, a decrease of up to
74 10% in this probability is expected, while in the other half an increase of up to 10% may be anticipated
75 (Figure 2). However, in some important cases the effect of climate change is stronger, especially for
76 maize in tropical regions. Here, the probability of yield gain with CA increases in about 72% of the
77 cropping area, with a larger than 10% gain for 30% of the maize cropping area (Figure 2c). An increase
78 in yield gain is also estimated for more than 50% of the cropping area for rice and sorghum in tropical
79 regions (Figure 2d, Figure 2f) and for sorghum in continental regions (Figure 2e).

80 To gain further insight into the conditions suitable for CA, partial dependence plots [16] - a common
81 approach used in machine learning to visualize the marginal effect of one or two inputs on the predicted
82 outcome[17] - were generated. The probability of yield gain with CA increases with decreasing PB, while
83 the effect of temperature appears more complex (S2) since the relationship among yield gain, PB and
84 Tave is not linear (Figure 3). Thus, the variation of CA performance in the future will depend on the
85 current level of PB and Tave and the direction and magnitude of the change in these two drivers. The
86 2D partial dependence plot of Figure 3 can help project changes in the performance of CA for a given
87 location or region based on their current levels of PB and Tave and their anticipated variations. For
88 example for maize, the increased temperature and relatively stable PB anticipated under climate change

89   scenario RCP 4.5 in tropical regions (depicted by the continuous and dashed boxes in Figure 3) would
90   lead to an increased probability of yield gain with CA, which is consistent with the results of Figure 2c.

91   Probabilities of yield gain with CA show important geographical variations under both current and
92   future climate conditions, in particular for maize (Figure 4) but also for other crop species (S3a-g).
93   Yield gains with CA are more likely in relatively higher latitude regions (> 40 Deg.) than lower
94   latitudinal bands for barley, cotton, rice, sorghum, soybean, sunflower, and wheat (S3), in line with the
95   results showed on Figure 1. For maize, the probability of yield gain from CA is less than 0.4 in
96   Laurentian Plateau in Canada, northcentral and northeast of the US, Brazilian Highlands, north part of
97   Western Europe and east part of Eastern Europe, Central Asia and northeast of China. For this crop, the
98   probability of yield gain is higher than 0.5 in Arid West of the US, most of the regions in Mato Grosso
99   and part of Amazon Basin in Brazil, the southern part of west Africa, north of India, and North China
100   Plain (Figure 4). For other crop species, CA has a higher chance to lead to a yield loss compared to CT
101   in the tropical regions, south of China (S3a-g), and north of India (S3a-f). For rice, sorghum, sunflower,
102   wheat cropped in Atlantic and Gulf Coastal Plain in the US, CA is also likely to lead to a yield loss
103   (S3c, S3d, S3f, S3g). Finally, CA has higher chance to outperform CT in several major cropping areas
104   of barley, sunflower and wheat (S3a, S3f, S3g; S5a, S5g, S5h).

105   The maps reporting the differences of yield gain probabilities between current and future climate
106   conditions (Figure 5 and S4) reveal important geographical disparities in the effects of climate change
107   on the chances of yield gain with CA. Under climate change scenario RCP 4.5, the probability of yield
108   gain is expected to increase in most of the northcentral and northeast of the US for barley, maize,
109   sorghum, soybean, sunflower, and wheat (S4a, S4d-g, Figure 5); In most of the central-west region and
110   Amazon Basin region in Brazil, Western Africa, and South Pacific Asia for maize, rice, and soybean
111   (S4c, S4e, Figure 5); In India for cotton, maize, rice, sorghum, soybean, sunflower (S4b-f, Figure 5); In
112   most of the north part of Central and Eastern Europe for barley, maize, sorghum, soybean, sunflower
113   and wheat (S4a, S4d-g, Figure 5); In northeast China for rice, sorghum (S4c, S4d). While the overall
114   performance of CA will decrease in the future in the US between 30- to 40-degree latitude for the barley,
115   maize, cotton, rice, sorghum, soybean, and sunflower (S4a-f, Figure5); In most temperate regions in
116   South America, including Uruguay, south of Brazil, and north of Argentina for barley, cotton, maize,
117   rice, sorghum, and sunflower (S4a-d, S4f, Figure 5); In the southern part of east Europe and northwest
118   Asia for Barley, soybean, sunflower and wheat (S4a, S4e-g); In south China for cotton, rice, sorghum,
119   sunflower (S4b-d, S4f).

120   To assess the robustness of our conclusions, we analyzed the sensitivity of our results to four different
121   climate models and RCP scenarios (S6). To summarize the response of our model to these choices, we
122   plotted the fractions of global cropping areas corresponding to increasing levels of yield gain probability
123   (from -0.1 to 0.2). The choice of the climate models had very little impact on the results (S6i-p),
124   although the results obtained with Hadgem2-es, and Ipsl-cm5a-lr are somewhat more extreme than
125   those obtained with Gfdl-esm2m and Miroc5. The sensitivity to the climate change scenarios was more
126   important (S6a-h). Although the main conclusions remain similar across all RCP scenarios, the stronger
127   changes of probability of yield gain are obtained under RCP 8.5 compared to RCP 6.0, RCP 4.5, and
128   RCP 2.6 (S6a-h), in particular the changes of yield gains become higher for maize and rice under RCP
129   8.5.

130   **Discussion**

131   Compared to previous studies on the productivity of CA[5–7,18], this is the first time that the probabilities
132   of yield gain with CA systems have been mapped in current and future climate scenarios. Thus, our
133   results offer meaningful and new information for policymakers, agricultural extension services, and
134   farmers. Relying on a global experimental dataset, we were able to identify favorable and unfavorable
135   climatic conditions and geographical regions for the implementation of CA for eight major staple crops
136   under current and future climate conditions. Some of the most promising geographical regions in our

137   analysis had also been identified in previous studies[18], but we were able to report information on yield
138   gains as probabilities instead of the simple categories of yield increase or decrease. More importantly,
139   none of the previous meta-analyses addressed the effect of future climate change scenarios on the
140   performance of CA and its geographical patterns. For most crops, CA outperformed CT in continental,
141   arid and temperate regions, but proved less suitable in tropical regions. This overall pattern is in line
142   with previous work [6]. We also show that there is higher chance of yield gain from CA under dryer
143   conditions, compared to wetter environments [5–7,18]. This is likely due to CA improving soil aggregate
144   stability via crop residue returns to soils, which reduces soil evaporation and surface runoff, and
145   maintains a higher level of soil moisture content compared to CT [19–27]. This competitive advantage of
146   CA comes into play for dryer climate conditions[28–33] , but does not apply in wetter and cooler
147   environment (S2a-c, S2f-i) where the soil evaporation is less intense. In tropical regions, CA is
148   commonly associated with waterlogging especially with poorly drained soils[5,6,27] which can result in
149   substantial yield losses. Air temperature also influences the performance of CA, but its effect appears
150   complex variable across crop species. Previous studies reported that permanent soil cover or residue
151   retention tends to lower soil temperature under warm conditions, but this trend can be reversed under
152   cold conditions because of soil cover acting as an insulation barrier[22,34,35]. As a result, CA may reduce
153   the negative impact of extreme air temperature events on crop yields, but this effect can be either
154   positive or negative depending on crop types, cultivars and development stages. Lower soil
155   temperatures may delay crop establishment and growth[27,36,37] and have a negative effect on crop yield[38–
156   40], but lower soil temperature has a positive impact on crop yield under arid conditions[36,37].

157   CA systems can dramatically improve biodiversity, increase the soil organic matter, and bring a lot of
158   positive environmental externalities such as reduced soil erosion, improved soil quality and enhanced
159   carbon sequestration [2,3,41]. Moreover, CA can provide a buffer effect to mitigate the impacts from more
160   intense rainstorms, more frequent droughts and increased daily temperature ranges, which can
161   significantly increase the crop resilience towards the changing climate and increase the stability of crop
162   yields[42,43]. Although CA is associated with a high probability of yield loss in many regions, we also
163   showed that, under future climate conditions, the relative productive performance of CA is expected to
164   increase for several crop species. This is especially true for maize in tropical regions, which further
165   strengthens the competitiveness of CA for this staple crop. Our results thus support the idea that CA
166   will be a relevant option for cropping systems in the future, capable of ensuring a long-term, sustainable
167   agricultural production for some key cropping areas[44,45].

Methods

Data collection

The literature search was done in February 2020 using the following keywords 'Conservation agriculture / No-till / No tillage / Zero tillage' & 'Yield / Yield change' in the websites 'ScienceDirect' and 'Science Citation Index (web of science)'. A total of 1012 potentially relevant papers were identified by reviewing the title and abstract, these papers were then screened according to the procedure summarized in S7. In the end, 422 papers left (published between 1983 to 2020), and 4071 paired yield observations from NT (including CA and NT without crop rotation or/and residue retention) and CT were collected from those papers, including 8 major crop species (369 observations for barley, 94 observations for cotton, 1580 observations for maize, 169 observation for rice, 145 observations for sorghum, 552 observations for soybean, 60 observations for sunflower, 1122 observations for wheat) in 51 countries (S8) from the experiment year 1980 to 2017. We also retrieved from the papers the information of crop type, year and location of the experiments, and agricultural management activities including crop irrigation (crop irrigated vs. rainfed), the application of fertilizers (field fertilized vs. unfertilized), the management of weed and pest (controlled vs. non-controlled), crop rotation (rotated vs. monoculture) and the management of crop residues (retained vs. removed). Additional data were extracted from several external databases, pertaining to crop growing season [13], soil texture [46] and climate factors such as precipitation (P) [9], minimum temperature (Tmin) [10], average temperature (Tave) [9], maximum temperature (Tmax) [10] and potential evapotranspiration (E) [11,12] in the growing season [13] in a particular year, and the precipitation balance (PB) was defined as precipitation minus total evapotranspiration, which indicated the water availability in the growing season. These data were obtained at a spatial resolution of $0.5° \ latitude \ \times 0.5° \ longitude$, and if the source data were in a finer spatial resolution, they were downscaled to the resolution of $0.5° \ latitude \ \times 0.5° \ longitude$.

Model training and cross-validation

The machine learning algorithm random forest [14] was trained to analyze the yield ratios of NT (including CA and NT without crop rotation or/and residue retention) vs. CT as the function of climatic variables, crop types, soil textures, and agricultural management activities. The climatic variables during the growing season such as PB, Tmin/Tave/Tmax were defined as numerical inputs, while crop type, soil texture, and agricultural management activities including crop irrigation, field fertilization, control of pests and weeds, crop rotation and crop residue management were defined as categorical inputs. The model output was expressed as the probability of yield gain from NT (including CA and NT without crop rotation or/and residue retention) vs. CT. The performance of the algorithm was assessed by estimating the area under the ROC curve by leave-one-out cross validation (LOOCV) (AUC=0.782, see S9). Since the inputs related to crop rotation and crop residue management were included in the model, it was possible to map the probability of yield gain for CA systems when combining NT, crop rotation and crop residue management. Maps were generated for all crop species at a spatial resolution of $0.5° \ latitude \ \times 0.5° \ longitude$.

Importance and partial dependence plots

Precipitation balance and average temperature appeared to be the most influential input parameters in the importance ranking obtained from our random forest algorithm (S10). We thus drew 2D partial dependence plots relating the probability of yield gain with CA (NT with crop rotation and residue retention) to PB and Tave, on a crop-by-crop basis. The detailed procedure implemented to produce 2D partial dependence plots is described in the flow chart reported in S11.

Global projection

The fitted random forest model was used to estimate the probability of yield gain from CA (NT with crop rotation and residue retention) for each grid cell located in cropping regions under current (2011-

214 2020) and future (2051-2060) climate scenarios. The monthly-average values of the climatic variables
215 (PB, Tmin/Tave/Tmax) were calculated in each grid cell over the two time periods considered, and then
216 these data were used to calculated the climatic variables during the growing season based on the crop
217 calendar database[13] (assume no change in current and future scenario). All the climatic data in both
218 current and future scenarios were obtained from four climate models: Gfdl-esm2m, Hadgem2-es, Ipsl-
219 cm5a-lr, and Miroc5, and 4 RCP scenarios: RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5. This results in
220 32 combinations (4 climate models x 4 RCP scenarios x 2 periods). We mainly focused on the Ipsl-
221 cm5a-lr model and RCP 4.5 scenario in the baseline simulations, because of their importance and similar
222 role in the protocol of ISIMIP2b project[47]. However, results from all combinations were analyzed and
223 shown in S6. All the climatic data can be downloaded through the website of Lawrence Livermore
224 National Laboratory [48].

225 We did not change the categorical inputs describing cropping practices between current and future
226 scenarios. The global soil texture was set based on HWSD dataset[46]. To estimate the performance of
227 CA vs. CT, we set the agricultural management activities as crop rotated, crop residue retained. As for
228 other agricultural management practices, the field was set to be fertilized, and with the control of pest
229 and weed. As for crop irrigation, it was set based on the crop irrigation mask from MIRCA2000 dataset
230 [49]. When more than 50% of the area in a grid cell were under rainfed conditions for a given crop in the
231 MIRCA2000 database, then this cell was considered as non-irrigated for this crop, and vice versa. See
232 S1 for the details of model settings. The model outputs were mapped at a spatial resolution of
233 $0.5° \, latitude \times 0.5° \, longitude$ based on the MIRCA2000 crop mask database[49]. Accumulated area
234 fractions under different levels of yield gain probability and different levels of probability change
235 between current and future scenarios were computed at the global scale and in different climate regions.

Climate regions

237 The "global" indicated the global cropping region for each crop[25]. According to the Köppen-Geiger
238 classification [15] and its nomenclature. The "tropical climate" included the regions with the climate types
239 Af, Am, As, Aw [15]. The "arid climate" included the regions with the climate types Bwk, Bwh, Bsk, Bsh
240 [15]. The "temperate climate" included the regions with the climate types Cfa, Cfb, Cfc, Csa, Csb, Csc,
241 Cwa, Cwb, Cwc [15]. The "continental climate" included the regions with the climate types Dfa, Dfb, Dfc,
242 Dfd, Dsa, Dsb, Dsc, Dsd, Dwa, Dwb, Dwc, Dwd [15].
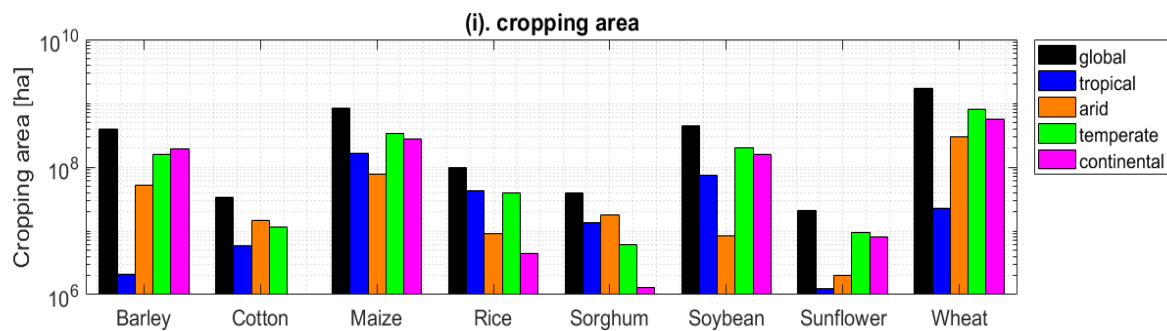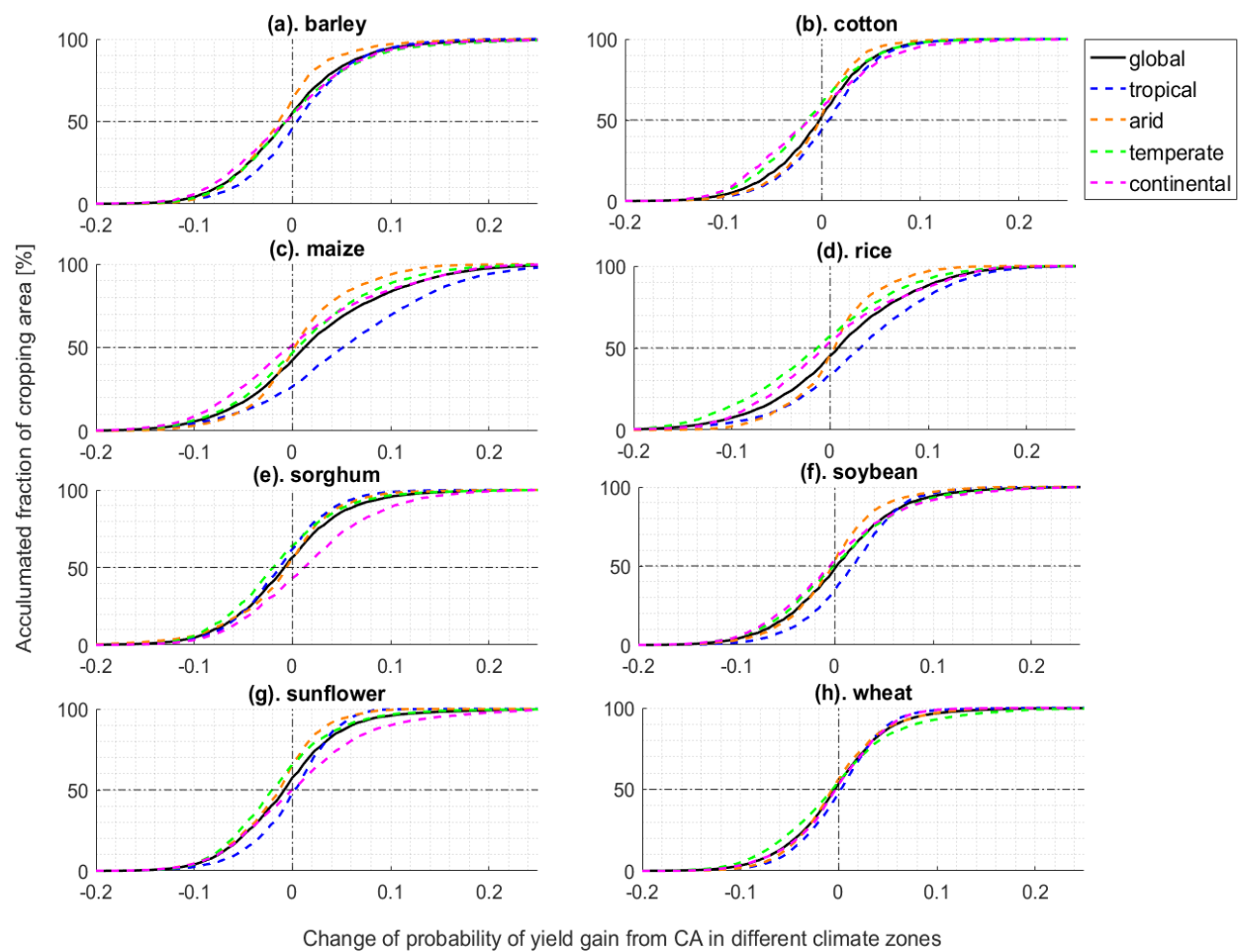
Figures

Figure 1
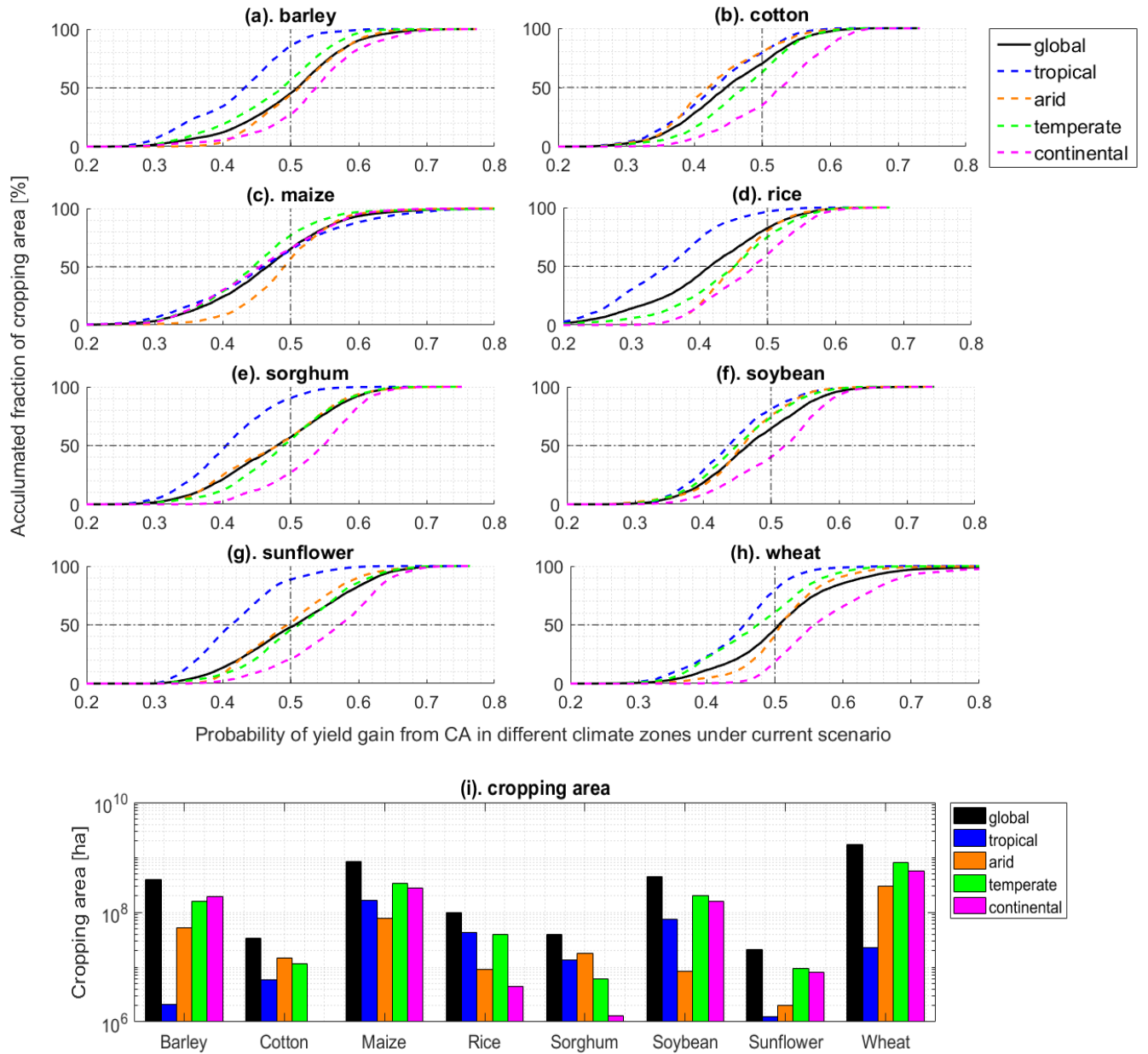
Accumulated fraction of the cropping area as a function of the probability of yield gain from CA (with field fertilization, and the control of weed and pest) for eight major crops (a-h) and different climate zones. The results are based on the average climate conditions over 2021-2020 according to the Ipsl-cm5a-lr climate model and RCP 4.5 scenario. The cropping areas in the main climate zones are given in (i).
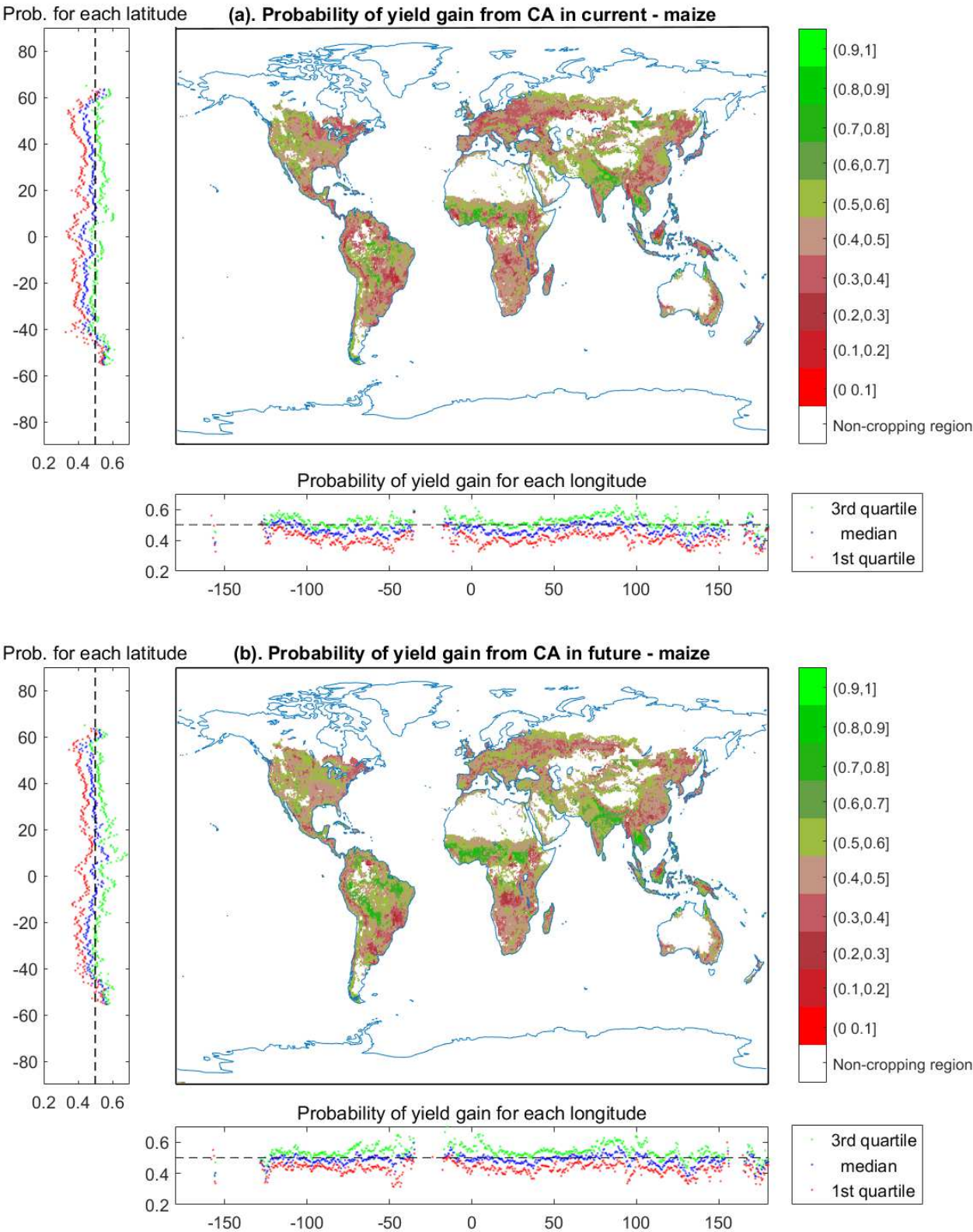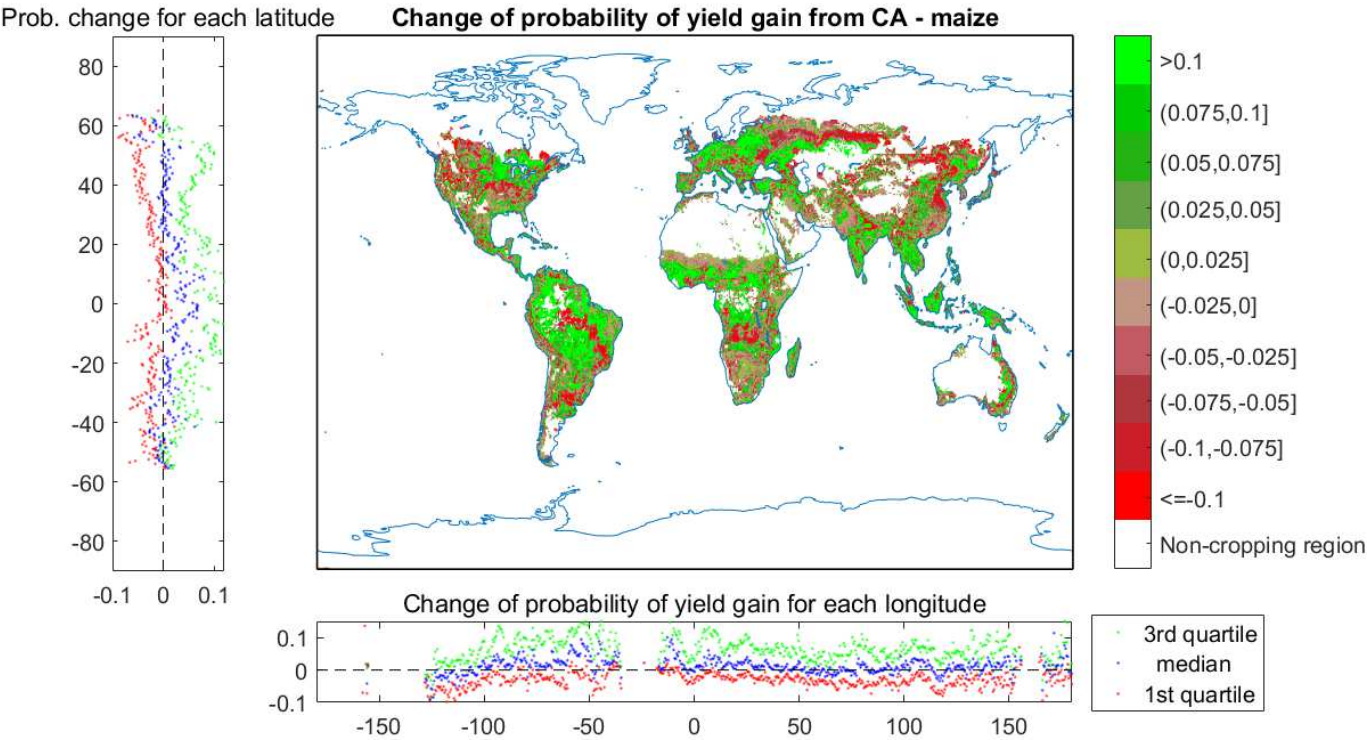
251   Figure 2

Accumulated fractions of the cropping area for different levels of change in the probability of yield gain from CA (with field fertilization, and the control of weed and pest). The results are based on the mean climate conditions in 2021-2020 for current scenario and 2051-2060 for future scenario (Ipsl-cm5a-lr climate model and RCP 4.5 scenario).

257   Figure 3

Partial dependence plot of maize in tropical region
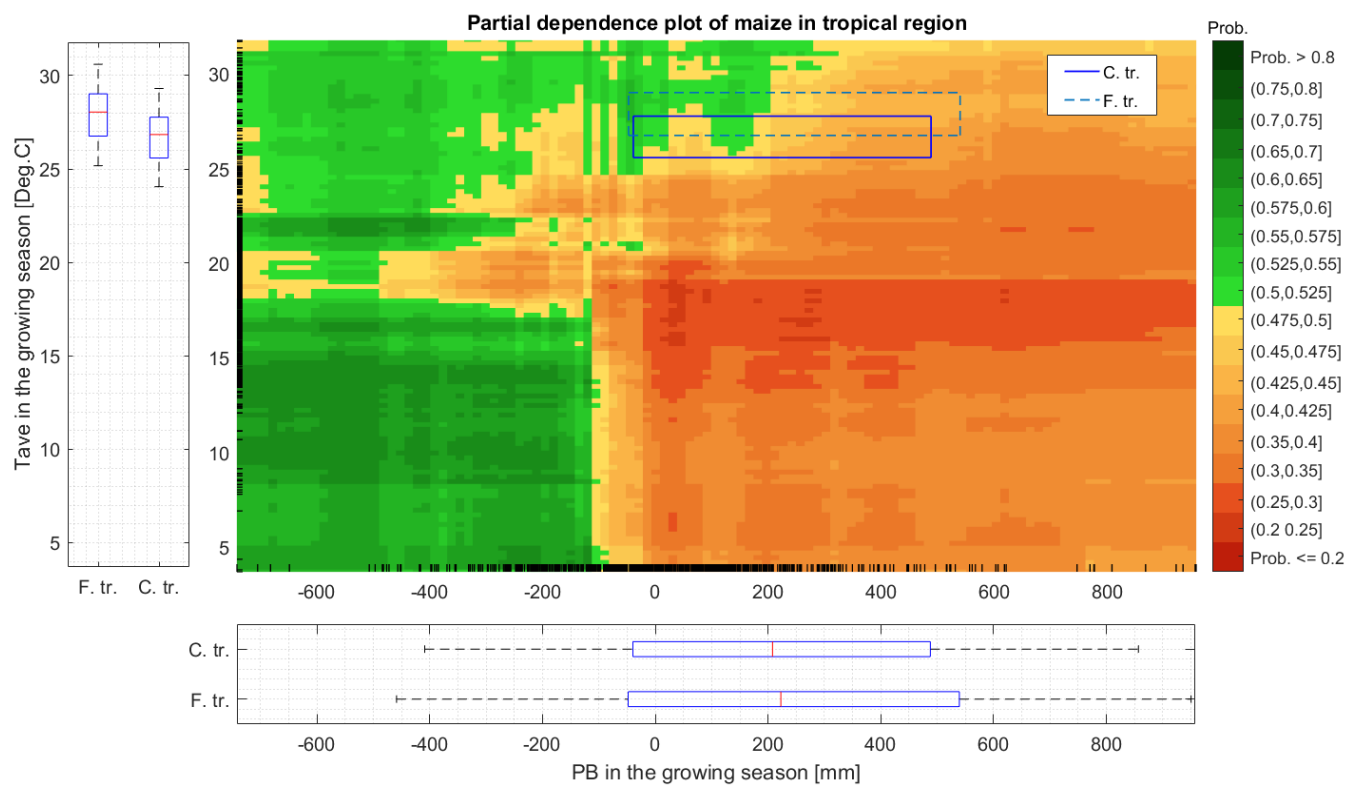
258

259   *2D partial dependence plot for maize. The green color indicates that the probability of yield gain from CA is higher than 0.5,*
260   *while the red means that the probability is lower than or equal to 0.5. The ticks on x-axis and y-axis are the observations of*
261   *PB and Tave, a more reliable response can be expected in zones with high numbers of observations. The box plots show the*
262   *distribution of PB and Tave in maize cropping areas with tropical climate. "F." means future, "C." means current, "tr."*
263   *means tropical. The box with continuous lines in the partial dependence plot shows the 1st and 3rd quartile of the range of PB*
264   *and Tave under current climate conditions in the maize tropical area, while the box with dash lines shows the 1st and 3rd*
265   *quartile of the range of PB and Tave under future climate conditions in the maize tropical area.*

266   Figure 4

(a). Probability of yield gain from CA in current - maize

Prob. for each latitude

Probability of yield gain for each longitude

- 3rd quartile
- median
- 1st quartile

(b). Probability of yield gain from CA in future - maize

Prob. for each latitude

Probability of yield gain for each longitude

- 3rd quartile
- median
- 1st quartile

267

Probability of yield gain with CA for maize under current (a) and future (b) climate conditions. Those regions with the probability of yield gain lower than 0.5 were highlighted in red (and green shades when the probability was higher). The results are based on the mean climate condition in 2011-2020 (current) and 2051-2060 (future) from the Ipsl-cm5a-lr climate model and the RCP 4.5 scenario. The side plots showed the variations of 1st quartile (red), median (blue), and 3rd quartile (green) yield gain probability with latitude and longitude. Non-cropping region indicated both the regions without maize and the regions where climate data was unavailable.

274   Figure 5

The change of probability of yield gain with CA for maize in future climate conditions, regions with a decreasing trend are depicted in red, while those with an increase in yield gain probability are depicted in green. The results are based on the mean climate condition in 2011-2020 (current) and 2051-2060 (future) from Ipsl-cm5a-lr climate model and RCP 4.5 scenario. The side plots showed the variations of 1st quartile (red), median (blue), and 3rd quartile (green) change on the probability of yield gain with latitude and longitude. Non-cropping region indicated both the regions without maize cropped and the regions with unavailable climatic data.

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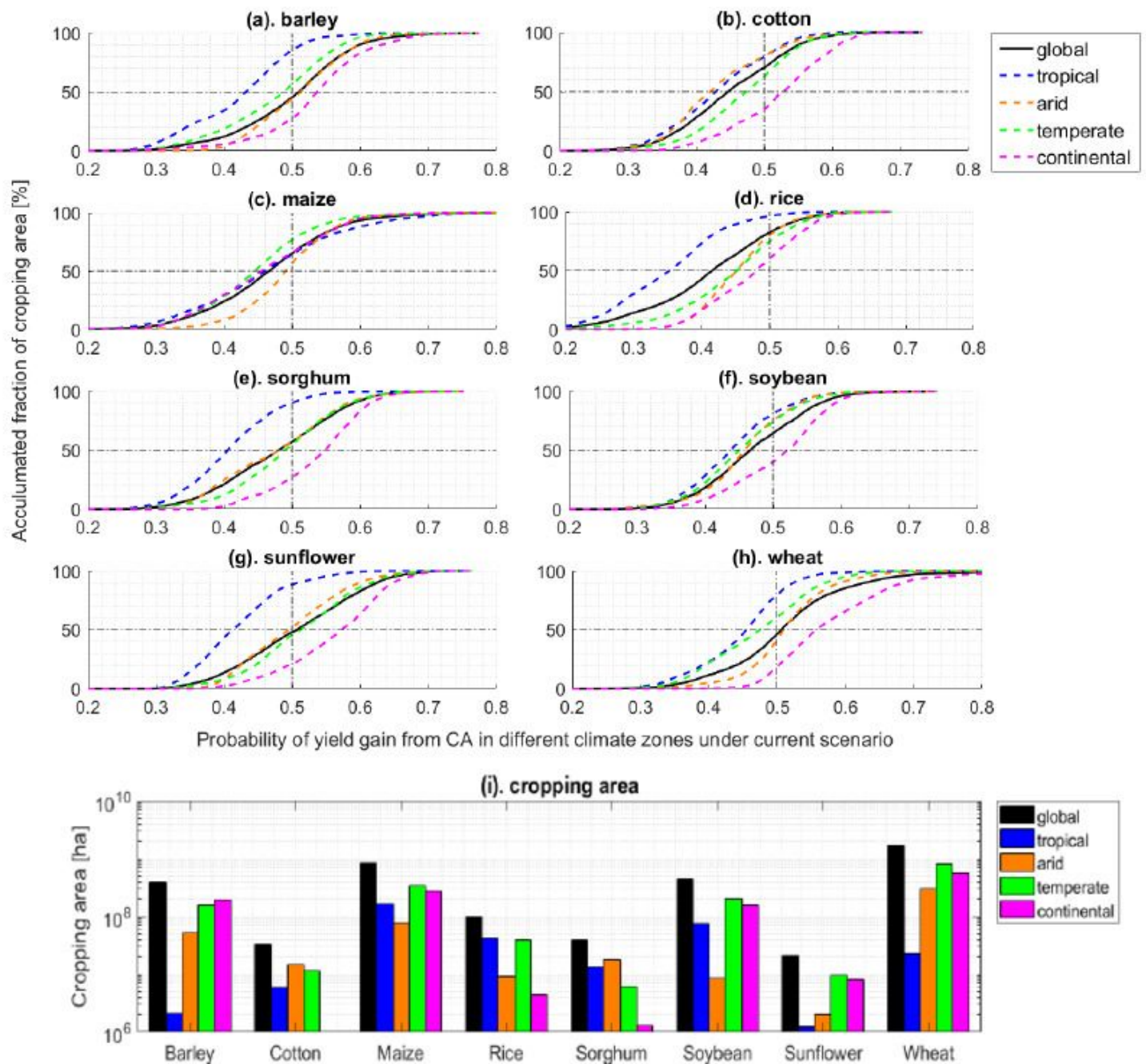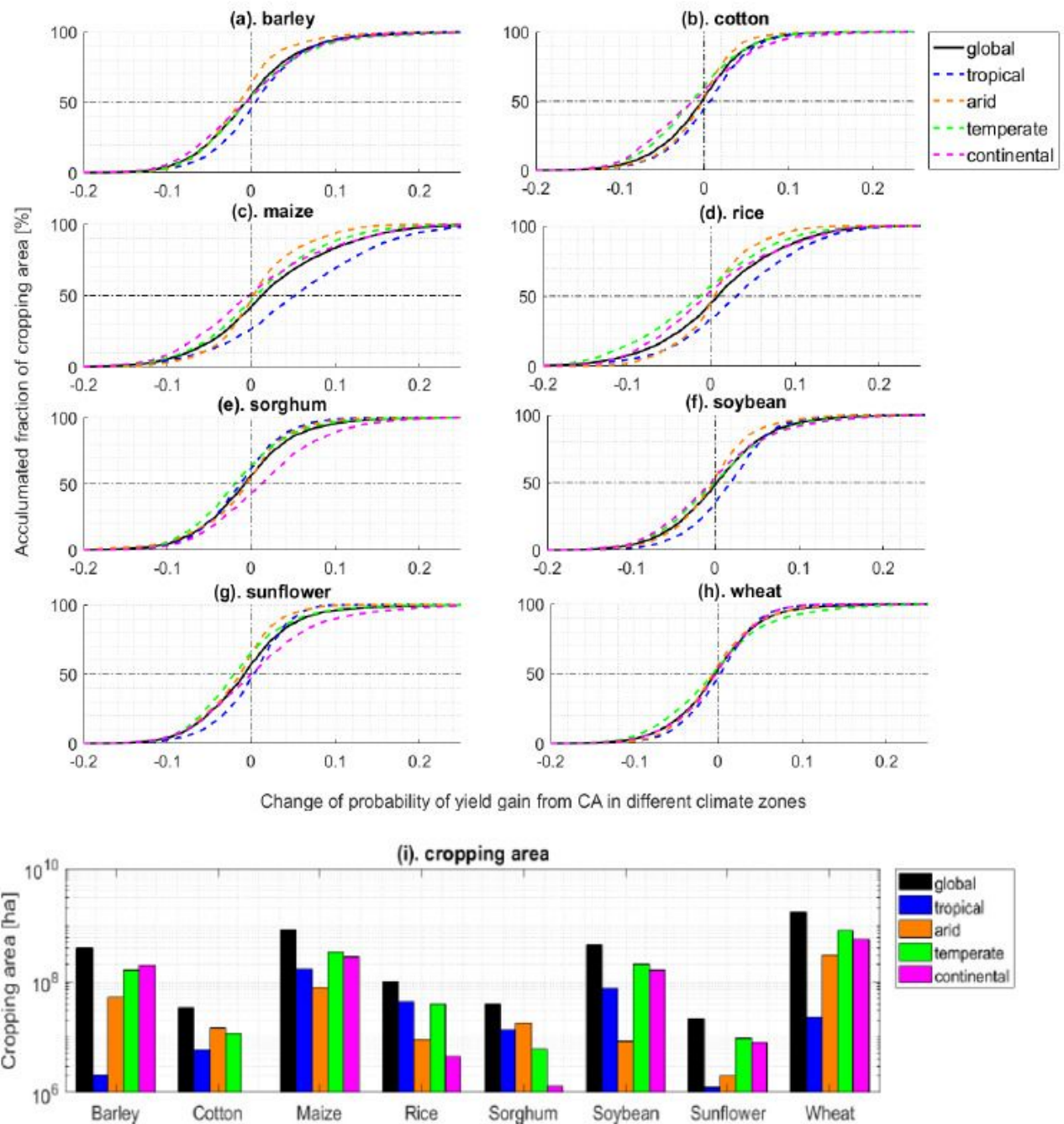398   modeling. *Global Biogeochemical Cycles* **24**, (2010).

399

Figures

Figure 1

Accumulated fraction of the cropping area as a function of the probability of yield gain from CA (with field fertilization, and the control of weed and pest) for eight major crops (a-h) and different climate zones. The results are based on the average climate conditions over 2021-2020 according to the lpsl-cm5a-lr climate model and RCP 4.5 scenario. The cropping areas in the main climate zones are given in (i).

Accumulated fractions of the cropping area for different levels of change in the probability of yield gain from CA (with field fertilization, and the control of weed and pest). The results are based on the mean climate conditions in 2021-2020 for current scenario and 2051-2060 for future scenario (Ipsl-cm5a-lr climate model and RCP 4.5 scenario).
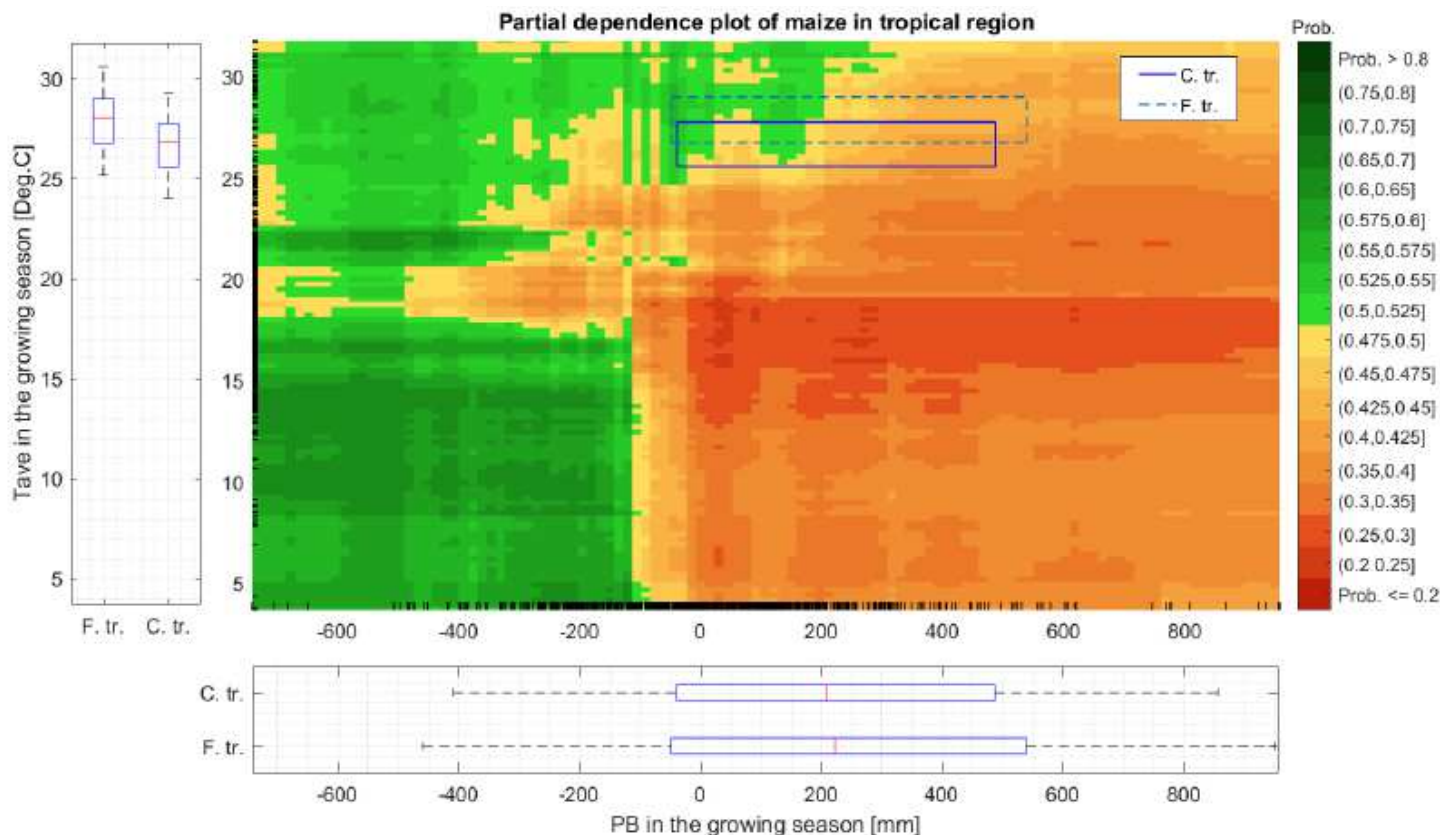
Figure 2

Accumulated fractions of the cropping area for different levels of change in the probability of yield gain from CA (with field fertilization, and the control of weed and pest). The results are based on the mean climate conditions in 2021-2020 for current scenario and 2051-2060 for future scenario (Ipsl-cm5a-lr climate model and RCP 4.5 scenario).

Figure 3

2D partial dependence plot for maize. The green color indicates that the probability of yield gain from CA is higher than 0.5, while the red means that the probability is lower than or equal to 0.5. The ticks on x-axis and y-axis are the observations of PB and Tave, a more reliable response can be expected in zones with high numbers of observations. The box plots show the distribution of PB and Tave in maize cropping areas with tropical climate. "F." means future, "C." means current, "tr." means tropical. The box with continuous lines in the partial dependence plot shows the 1st and 3rd quartile of the range of PB and Tave under current climate conditions in the maize tropical area, while the box with dash lines shows the 1st and 3rd quartile of the range of PB and Tave under future climate conditions in the maize tropical area.
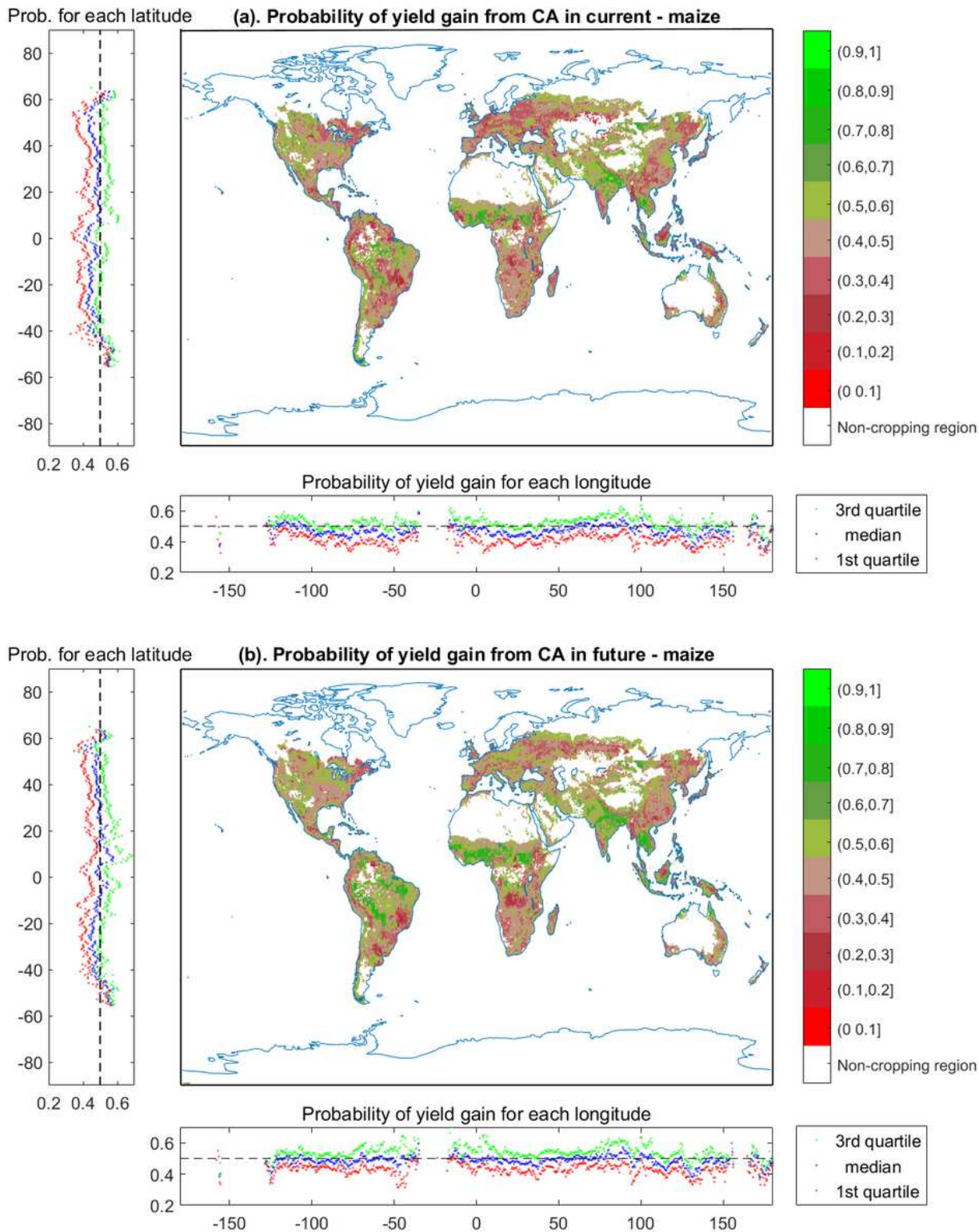
Figure 4

Probability of yield gain with CA for maize under current (a) and future (b) climate conditions. Those regions with the probability of yield gain lower than 0.5 were highlighted in red (and green shades when the probability was higher). The results are based on the mean climate condition in 2011-2020 (current) and 2051-2060 (future) from the lpsl-cm5a-lr climate model and the RCP 4.5 scenario. The side plots showed the variations of 1st quartile (red), median (blue), and 3rd quartile(green) yield gain probability

with latitude and longitude. Non-cropping region indicated both the regions without maize and the regions where climate data was unavailable.
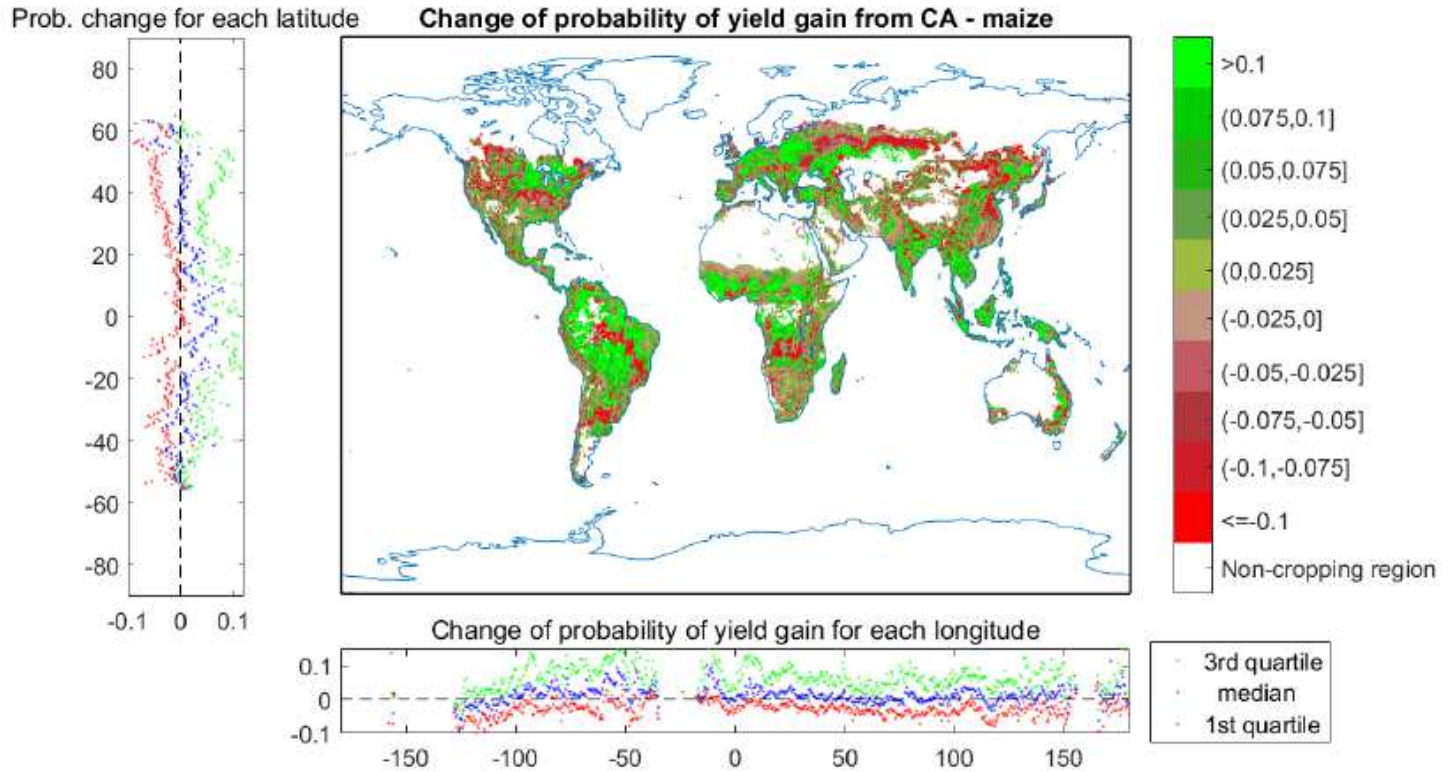

Figure 5

The change of probability of yield gain with CA for maize in future climate conditions, regions with a decreasing trend are depicted in red, while those with an increase in yield gain probability are depicted in green. The results are based on the mean climate condition in 2011-2020 (current) and 2051-2060 (future) from Ipsl-cm5a-lr climate model and RCP 4.5 scenario. The side plots showed the variations of 1st quartile (red), median (blue), and 3rd quartile (green) change on the probability of yield gain with latitude and longitude. Non-cropping region indicated both the regions without maize cropped and the regions with unavailable climatic data.

Supplementary Files

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