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The impact of climate change on the productivity of conservation agriculture

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Conservation agriculture (CA) is being promoted as a set of management practices that can sustain crop production while providing positive environmental benefits. However, its impact on crop productivity is hotly debated, and how this productivity will be affected by climate change remains uncertain. Here we compare the productivity of CA systems and their variants on the basis of no tillage versus conventional tillage systems for eight major crop species under current and future climate conditions using a probabilistic machine-learning approach at the global scale. We reveal large differences in the probability of yield gains with CA across crop types, agricultural management practices, climate zones and geographical regions. For most crops, CA performed better in continental, dry and temperate regions than in tropical ones. Under future climate conditions, the performance of CA is expected to mostly increase for maize over its tropical areas, improving the competitiveness of CA for this staple crop.

Conservation agriculture (CA) is a crop production system based on three principles: minimum soil disturbance (going as far as no tillage (NT)), permanent soil cover with crop residues and diversified crop rotation (with at least three crop species involved)[1]. In compliance with sustainability goals, CA is designed to sustain crop production in the long term while improving crop resilience to climate change and protecting the environment. Benefits of CA have been demonstrated in terms of enhancing soil carbon sequestration, improving soil quality, reducing soil erosion and increasing biodiversity[2,3]. However, since crop yield depends on many interacting factors, including local climate conditions[4], soil characteristics[5] and management practices[6], it is difficult to assess the potential of CA to increase agricultural productivity. Besides CA (as defined according to the above principles, which follow the Food and Agriculture Organization's (FAO) approach of CA; ref. [7]), this issue also applies to its variants such as NT without crop rotations and soil cover, NT with soil cover but no rotation and NT with rotation but no soil cover. On the basis of the findings of recent meta-analyses[5,6,8], these systems are likely to lead to a yield reduction[6] compared to conventional tillage (CT), except for regions facing water limitations. However, the heterogeneity of the experimental results on CA (and their variants) versus CT is very large and their outcome varies as a function of climate conditions[6] and management practices[6,8,9]. The studies of Pittelkow et al.[6,8] relied on a synthetic aridity index to characterize the climate, which makes it hard to analyse the response of CA productivity to interannual weather variability or to predict the impact of future changes in climate. To date, a comprehensive, global synthesis of the impact of climate change on the productivity of CA with respect to CT systems is still lacking.

Here we compared the crop yields of CA systems (and their variants) versus CT under current and future climate conditions on the basis of a new global database[10,11] of paired yield observations of CA (and their variants) versus CT. This dataset includes the most recently published experimental studies on this topic, a detailed description of agricultural management practices (including crop irrigation, fertilization, weed and pest control, soil cover management and crop rotation) and a broad set of climatic variables from external databases, such as precipitation (P)[12], minimum air temperature (T_{min})[13], average air temperature (T_{ave})[12], maximum air temperature (T_{max})[13] and potential evapotranspiration (E)[14,15] over the crop growing seasons[16]. As an indicator of water availability for crops, the precipitation balance (PB) was defined as ($P-E$) over the growing season[5].

A machine-learning model based on random forest[17] was trained and cross-validated on the basis of 4,403 paired yield data of CA (and its variants) versus CT from the dataset. The model was used to map the probability of yield gain from CA-like systems versus CT systems, $\left(\frac{\text{Yield}_{\text{CA or variants}}}{\text{Yield}_{\text{CT}}} > 1\right)$, considering different agricultural management practices successively (with/without soil cover, rotation, weed and pest control, irrigation, fertilization). The analysis was conducted at a spatial resolution of 0.5° latitude × 0.5° longitude on the basis of current (2011–2020) and future (2051–2060) average climate conditions for eight major crops worldwide (spring barley, cotton, maize, rice, sorghum, soybean, sunflower and winter wheat). For each crop, maps were then produced and compounded to derive the accumulated fractions of the cropping area achieving a given yield gain probability of CA versus CT under current climate conditions. Similarly, the accumulated fractions of the cropping area achieving a given level of change in this probability under future climate conditions were calculated. These fractions show the proportions of cropping area with low to high probabilities of yield gain from CA versus CT and with low to high changes for this probability under climate change. Both proportions were computed at the global scale and across different climate zones[18]. The results were used to evaluate the impact of crop management practices on the performance of CA, to identify the favourable and unfavourable climate zones for CA and to assess the climate change impact on the productivity of CA in different climate zones. The details of model setting for global projection are explained in the Methods and further detailed in Supplementary Table 1.

Our results show that, under current climate conditions, NT (in the absence of soil cover and rotation) is associated with a very low probability of yield gain compared to CT (Supplementary Fig. 1a4–h4 and 1a5–h5). CA shows better performance than NT

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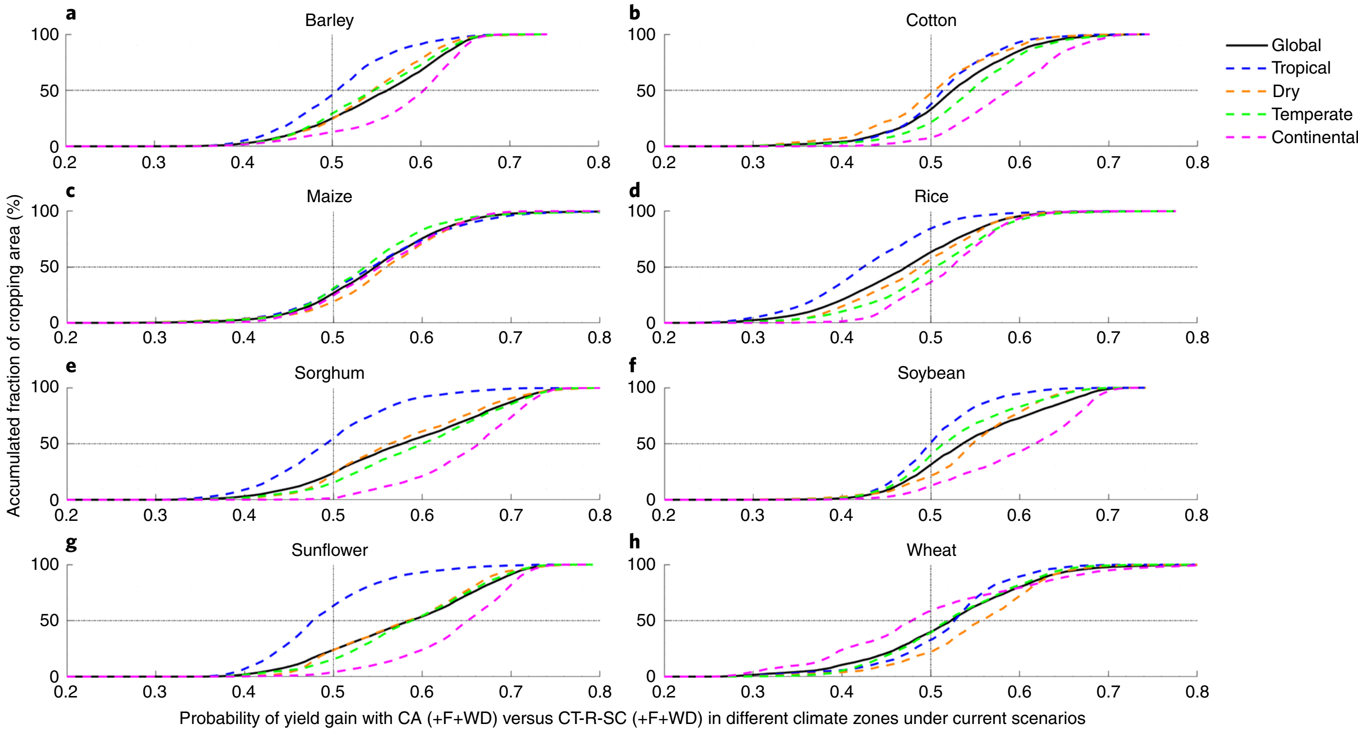

Fig. 1 | Accumulated fractions of cropping area achieving a given probability of yield gain with CA (+F+WD) versus CT–R–SC (+F+WD). a–h, Panels **a–h** indicate different crop species. **a**, Barley. **b**, Cotton. **c**, Maize. **d**, Rice. **e**, Sorghum. **f**, Soybean. **g**, Sunflower. **h**, Wheat. Different coloured lines represent the accumulated fractions of cropping area in different climate zones. The black line represents the global cropping areas for this crop, the blue line represents the cropping areas in the tropical region, the orange line represents the cropping areas in the dry region, the green line represents the cropping areas in the temperate region, and the purple line represents the cropping areas in the continental region. The results are based on the average climate conditions over 2021–2020 simulated by the Ipsl-cm5a-lr climate model and RCP 4.5 scenario. F, fertilization; R, crop rotation; SC, soil cover; WD, weed and pest control (see Methods).

due to the presence of soil cover and use of crop rotation but does not systematically outperform CT (Supplementary Fig. 1a1–h1 and 1a4–h4). With well-managed field fertilization and integrated weed and pest control, CA stands high chances of outperforming CT except in tropical regions (Fig. 1 and Supplementary Fig. 1a2–h2). The performance of CA is also slightly improved in non-irrigated fields, except in tropical regions (Fig. 1 and Extended Data Fig. 1).

For most of the studied crops, the overall probability of yield gain from CA is higher in continental, dry and temperate regions than in tropical regions (Fig. 1a,d–g and Supplementary Fig. 1a2–g2). The probability of yield gain with CA is particularly low for rice. For this crop, the probability of yield increase/gain is lower than 0.5 (which indicates a higher probability of yield loss) over about 60% of its global cropping area and in about 85% of its cropping area in the tropics (Fig. 1d and Supplementary Fig. 1d2).

For several crops and climate regions, the estimated effect of climate change on the probability of yield increase with CA is relatively moderate. Over approximately half of the cropping areas, a decrease of up to 10% in this probability is expected, while in the other half an increase of up to 15% may be anticipated (Fig. 2). However, in some important cases, the effect of climate change is stronger, especially for maize in tropical regions where the probability of yield gain with CA increases in about 70% of the cropping area. Besides, for more than 20% of the maize cropping area in this climate zone, the increase on the probability of yield increase is higher than 10% (Fig. 2c). An increase in yield gain is also expected for more than 60% of the cropping area for rice in dry regions and for soybean in tropical regions (Fig. 2d,f). This fraction rises to more than 70% of the cropping area for sorghum in continental regions (Fig. 2e).

Probabilities of yield gain with CA show important geographical variations under both current and future climate conditions for maize (Figs. 3 and 4) but also for other crop species (Supplementary Fig. 2). Yield gains with CA systems and their variants are more likely in relatively higher latitude regions (>40°) than lower latitudinal bands for barley, cotton, rice, sorghum, soybean and sunflower (Supplementary Fig. 3), in line with the results showed on Fig. 1. CA systems and their variants perform better in northwestern America, northwestern India, northern sub-Saharan Africa and southern Russia than in northeastern America, western and central Europe and the central part of sub-Saharan Africa (Fig. 3 and Supplementary Fig. 2). For maize, in the absence of fertilizer inputs and integrated weed and pest control, the probability of yield gain from CA is higher than 0.5 in dry areas of western United States, southern Russia, northern India and the North China Plain. The yield gain probability drops to 0.4 in the Laurentian Plateau of Canada, north-central and northeastern United States and part of western and central Europe (Fig. 3b). For other crop species, CA has a higher chance of leading to a yield loss compared to CT in the tropical regions (Supplementary Fig. 2a2–h2), southern China (Supplementary Fig. 2e2–h2), northeastern America and western and central Europe (Supplementary Fig. 2a2,e2,f2,h2). Conversely, when implemented with field fertilization and integrated weed and pest control, CA has a higher chance of outperforming CT in the major cropping areas for barley, sunflower and wheat (Supplementary Fig. 2a1,g1,h1 and Supplementary Fig. 5).

Our results also show that soil cover has a stronger (and positive) effect on yield gain probability than other management practices, such as fertilizer inputs, weed and pest control and crop rotation. Thus, without soil cover, NT systems show a lower probability of

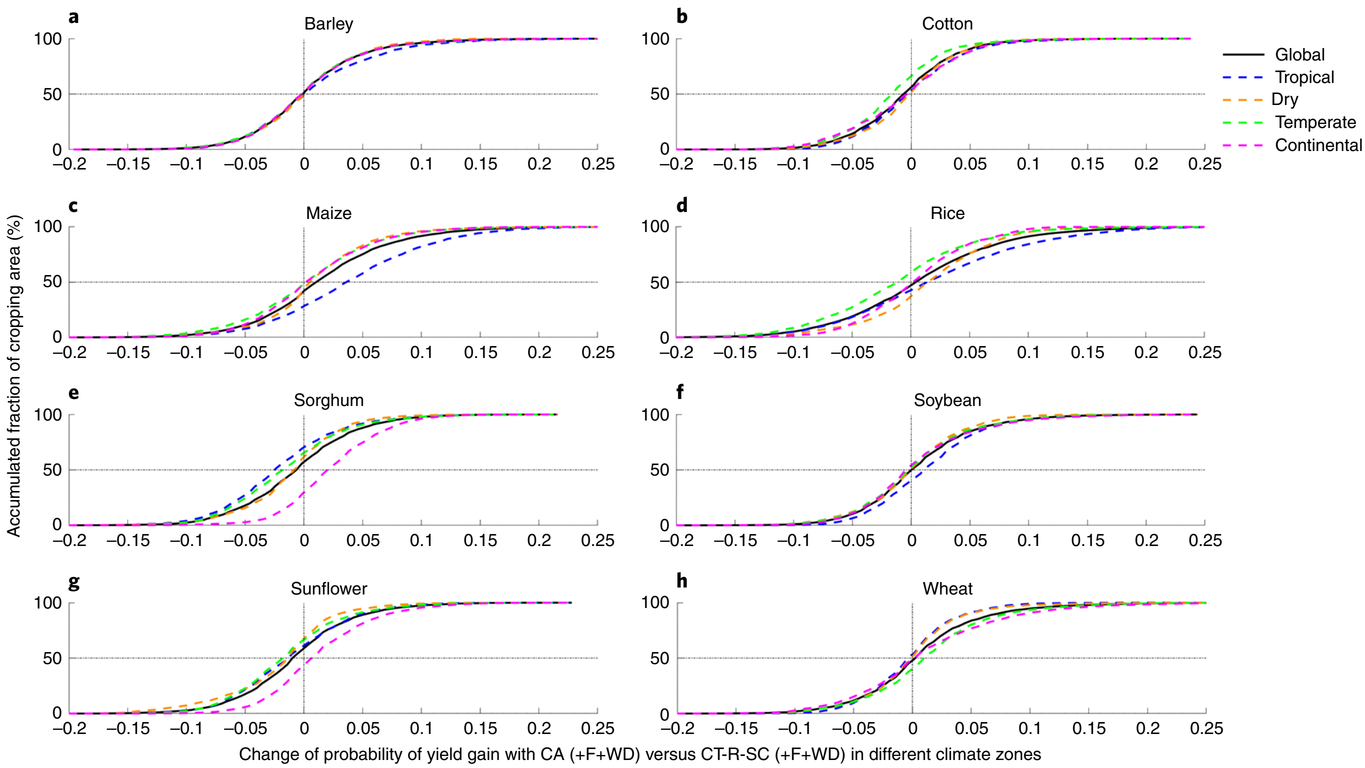

Fig. 2 | Accumulated fractions of the cropping area for different levels of change in the probability of yield gain with CA (+F+WD) versus CT-R-SC (+F+WD). a–h, Different crop species. **a**, Barley. **b**, Cotton. **c**, Maize. **d**, Rice. **e**, Sorghum. **f**, Soybean. **g**, Sunflower. **h**, Wheat. Different coloured lines represent different climate zones. The results are based on the mean climate conditions in 2021–2020 for the current scenario and 2051–2060 for the future scenario (Ipsl-cm5a-lr climate model and RCP 4.5 scenario). Change of probability corresponds to the difference between the probability under future climate and the probability under current climate.

yield gain than full-blown CA (Supplementary Fig. 2), which is in line with the input importance ranking obtained with our model (Extended Data Fig. 2). Note that, although management practices have a substantial impact on yield gain probabilities, they have limited influences on the geographical variations of these probabilities (Supplementary Fig. 1 and Supplementary Fig. 2).

The maps reporting the differences of yield gain probabilities between current (2010–2020) and future (2051–2060) climate conditions (Supplementary Table 1 gives projection details; Fig. 5 and Supplementary Fig. 4 give results) reveal important geographical disparities in the effects of climate change on the odds of yield gain with CA systems and their variants; we have noticed that climate change could have a positive effect in some regions for certain crop species. However, although the probability of yield gains with CA systems and their variants versus CT systems tended to increase under future climate scenarios, it remained below 0.5 in many regions. Under climate change scenario representative concentration pathway (RCP) 4.5, the probability of yield gain is expected to increase: in most of the northcentral and northeastern United States for barley, maize, sorghum, soybean and sunflower (Supplementary Fig. 4a1,e1,g1 and Fig. 5a); in most of the central-western region in Brazil together with the Amazon basin, western Africa and Asia-Pacific for maize, rice and soybean (Fig. 5a and Supplementary Fig. 4d1,f1); in many parts of India for cotton, maize, rice, sorghum, soybean and sunflower (Supplementary Fig. 4b1,d1–g1 and Fig. 5a); in most of Europe for barley, maize, sorghum, soybean, sunflower and wheat (Supplementary Fig. 4a1,e1–h1 and Fig. 5a); and in northeastern China for rice and sorghum (Supplementary Fig. 4d1,e1). Conversely, the overall performance of CA will decrease in the future in most temperate regions in South America, including Uruguay, southern Brazil and northern Argentina for barley, cotton, rice, sorghum and sunflower (Supplementary Fig. 4a1,b1,d1,e1,g1); in the south of Russia and northwest of Asia for barley, cotton, soybean and sunflower (Supplementary Fig. 4a1,b1,e1,g1); and in southern China for cotton, maize, rice, sorghum and sunflower (Supplementary Fig. 4b1,d1,e1,g1 and Fig. 5a). Crop management practices have limited influence on the estimated impact pattern of climate change on yield gain probability (Supplementary Fig. 1).

To assess the model sensitivity to climate models and climate change scenarios, we plotted the fractions of global cropping areas corresponding to increasing levels of yield gain probability (from −0.1 to 0.2) for four different climate models and RCP scenarios (Extended Data Fig. 3). The choice of the climate models had very little impact on the results (Extended Data Fig. 3i-p), although the results obtained with Hadgem2-es and Ipsl-cm5a-lr are somewhat more extreme than those obtained with Gfdl-esm2m and Miroc5. The sensitivity to the climate change scenarios was more important (Extended Data Fig. 3a–h). Although the main conclusions remain similar across all RCP scenarios, the stronger changes in yield gain probability are obtained under RCP 8.5 compared to RCP 6.0, RCP 4.5 and RCP 2.6 (Extended Data Fig. 3a–h). In particular, the changes of yield gains become larger for maize and rice under RCP 8.5.

In contrast to previous studies on the productivity of CA5,[5,6,8,19] here the probabilities of yield gain resulting from a shift from CT to several variants of CA systems have been mapped for current and future climate scenarios. Thus, our results offer meaningful and new information for policymakers, agricultural extension services and farmers. Relying on a global experimental dataset, we were able to identify favourable and unfavourable climate conditions and geographical regions for the implementation of CA systems for eight major staple crops under current and future climate conditions.

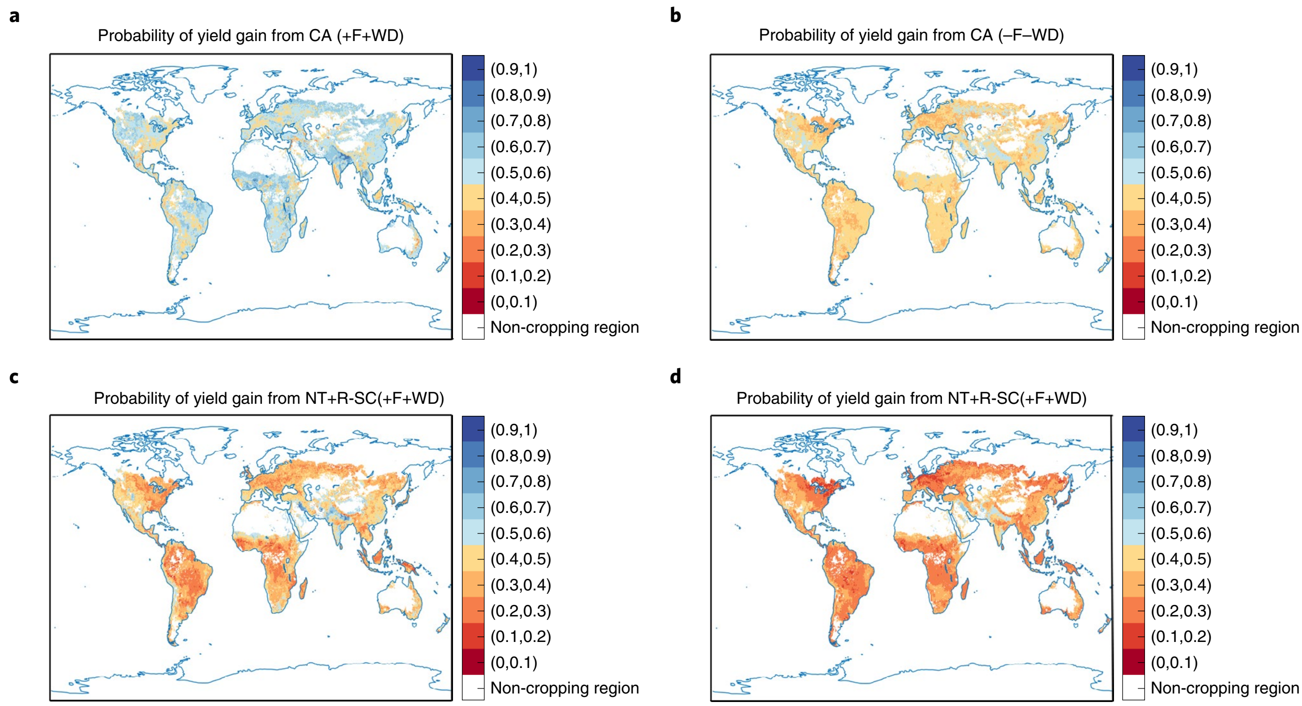

Fig. 3 | Probability of yield gain with CA and their variants versus CT for maize under current climate conditions. Probabilities in the form (0,0.1) indicate a range from 0 to 0.1 excluding 0 but including 0.1. **a**, The performance of CA (+F+WD) versus CT-R-SC (+F+WD). **b**, The performance of CA (–F–WD) versus CT-R-SC (–F–WD). **c**, The performance of NT+R-SC (+F+WD) versus CT-R-SC (+F+WD). **d**, The performance of NT-R-SC (–F–WD) versus CT-R-SC (–F–WD). Regions with a probability of yield gain lower than 0.5 are highlighted in red (and in blue shades when the probability was higher). Non-cropping region indicates both the regions without maize crops and regions where climate data were unavailable. The results are based on the average climate conditions over 2021–2020 simulated by the Ipsl-cm5a-lr climate model and RCP 4.5 scenario.

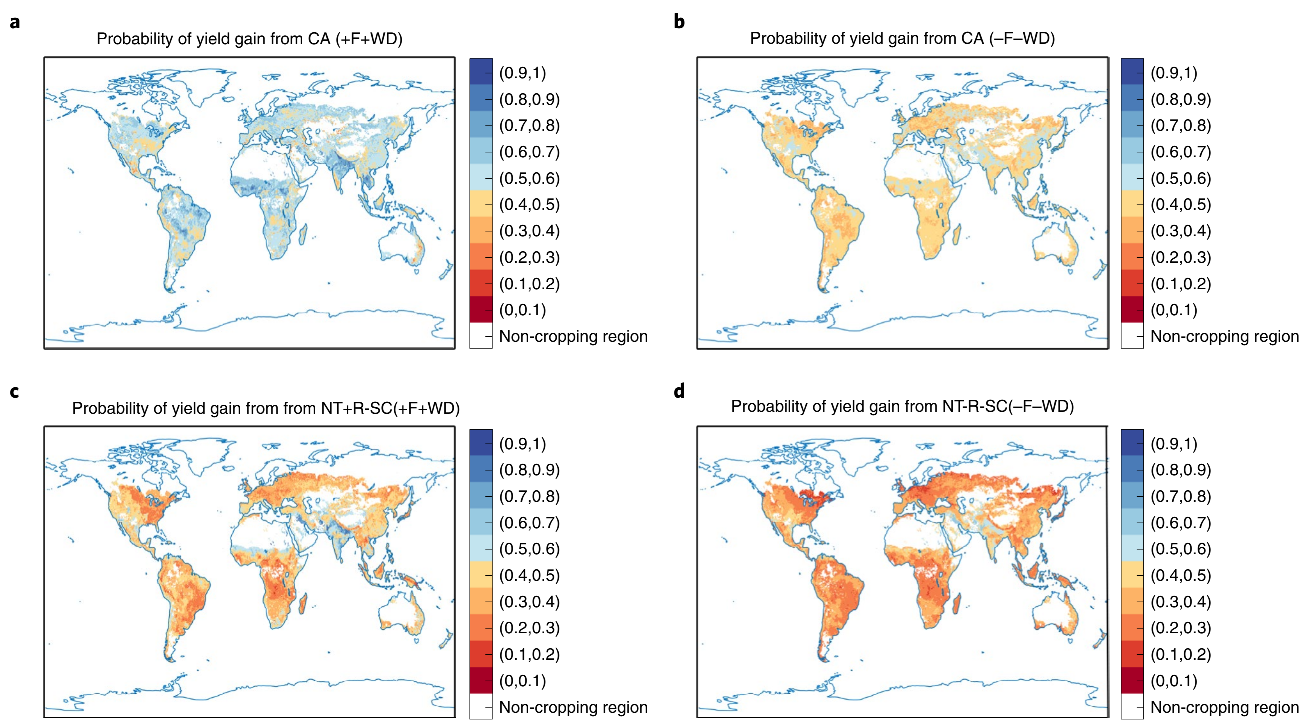

Fig. 4 | Probability of yield gain with CA systems and their variants versus CT for maize under future climate conditions. a, The performance of CA (+F+WD) versus CT-R-SC (+F+WD). **b**, The performance of CA (–F–WD) versus CT-R-SC (–F–WD). **c**, The performance of NT+R-SC (+F+WD) versus CT-R-SC (+F+WD). **d**, The performance of NT-R-SC (–F–WD) versus CT-R-SC (–F–WD). Regions with a probability of yield gain lower than 0.5 are highlighted in red (and in blue shades when the probability was higher). Non-cropping region indicates both the regions without maize crops and regions where climate data were unavailable. The results are based on the average climate conditions over 2051–2060 simulated by the Ipsl-cm5a-lr climate model and RCP 4.5 scenario.

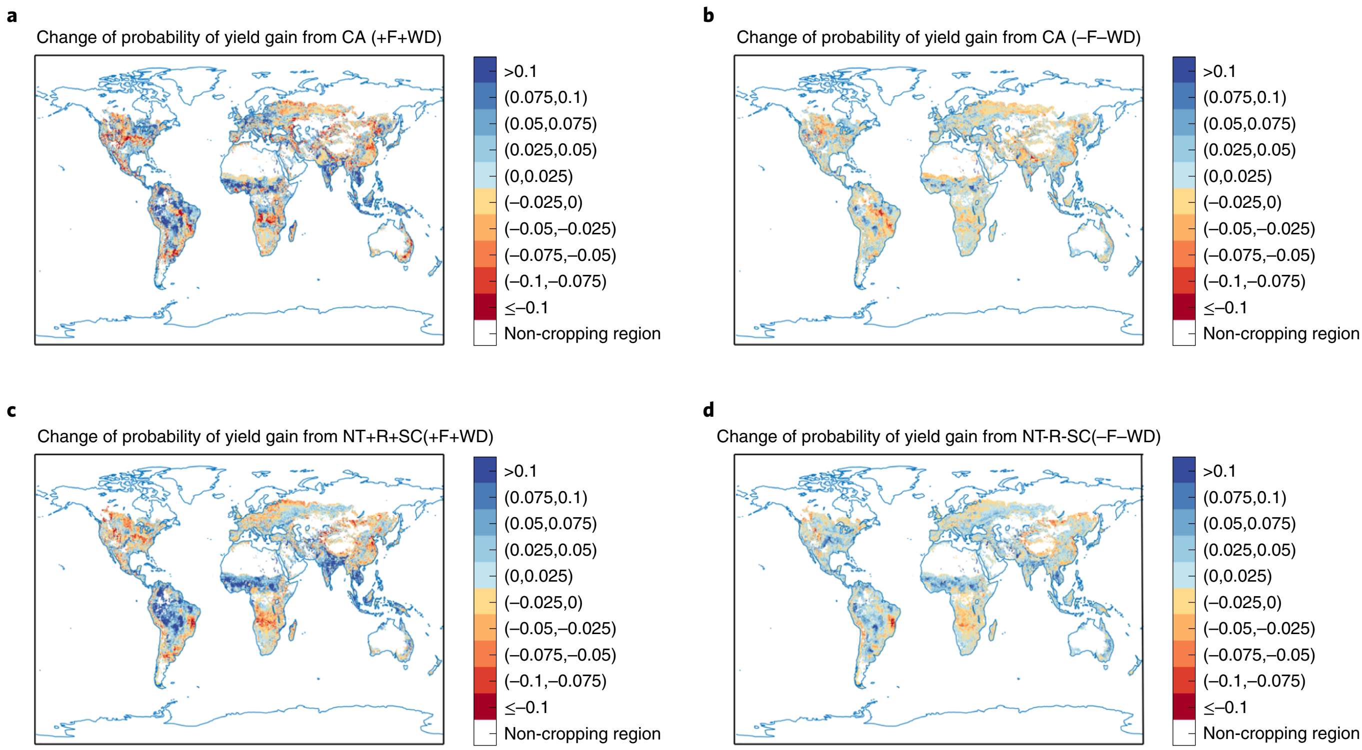

Fig. 5 | The change of probability of yield gain with CA and their variants versus CT for maize under climate change (future versus current). **a**, The change of probability of yield gain with CA (+F+WD) versus CT-R-SC (+F+WD) under climate change. **b**, The change of probability of yield gain with CA (-F-WD) versus CT-R-SC (-F-WD) under climate change. **c**, The change of probability of yield gain with NT+R-SC (+F+WD) versus CT-R-SC (+F+WD) under climate change. **d**, The change of probability of yield gain with NT-R-SC (-F-WD) versus CT-R-SC (-F-WD) under climate change. Regions with a decreasing trend are depicted in red, while those with an increase in yield gain probability are depicted in blue. The results are based on the average climate conditions over 2011–2020 (current) and over 2051–2060 (future) simulated by Ipsl-cm5a-lr climate model and for the RCP 4.5 scenario. Non-cropping region indicates both the regions without maize crops and regions where climate data were unavailable.

Some of the most promising geographical regions in our analysis had also been identified in previous studies[19] but we were able to report information on yield gains as probabilities instead of simpler increase or decrease categories. More importantly, we addressed the impacts of future climate change scenarios and different agricultural management practices on the performance of CA systems and their geographical patterns.

However, there are also limitations in our study. Due to the lack of global quantitative data on crop irrigation, this study was taken into account in our models as a categorical variable. Although a large part of the data considered in this study was collected under humid climate conditions, a substantial amount of data was obtained in dry regions under rainfed or irrigated conditions. In this study, climate and soil data were extracted from external databases and not from the collected articles because these data were missing or not reported consistently in the individual articles. Consequently, these data might not always match experimental records. The use of external databases has the added benefit of helping us understand how inter- and intra-annual climate variability affects the productivity of CA systems and their variants versus CT. It is also required to predict the performance of these systems under future climate conditions. Data availability may affect model accuracy. Due to the limited number of observations for these crops, the conclusions obtained for rice and sunflower are more uncertain compared to other crops (Supplementary Fig. 7). Despite these limitations, the results of our model assessment via the cross-validation are overall satisfactory (Methods and Supplementary Fig. 7).

We showed that soil cover has a strong positive effect on probability of yield gain. Without soil cover, NT systems are likely to lead to a yield loss compared to CT (Supplementary Fig. 2a3–h3). Soil cover reduces soil evaporation and surface runoff and maintains a high level of soil moisture content[20–28], thus increasing the competitiveness of CA systems especially for dryer climate conditions[29–34]. Therefore, keeping the soil covered by crop residues appears to be an important factor for the success of CA systems. However, in practice, maintaining crop residues might be challenging in some regions, such as Africa, where the crop residues are used to feed livestock[35]. In such situations, a possible solution would be to rely on alternative sources of plant materials, such as residues from cover crops, grass, leaf litter from trees, sawdust and so on[35]. Without soil cover, NT has low chance to entail yield gains compared to CT. Under future climate scenarios, the performance of NT is expected to improve in the north of sub-Saharan Africa for maize (Fig. 5c) and sorghum (Supplementary Fig. 4e1) but the probability will remain lower than or close to 0.5.

Although less influential, other farming practices appear to increase the probability of yield gain of CA, in particular fertilization and weed and pest control. Thus, for most crops, CA with field fertilization and weed and integrated pest control outperformed CT in continental, dry and temperate regions but proved less suitable in tropical regions (Supplementary Fig. 1a1–h1 and Supplementary Fig. 2a1–h1). This overall pattern is in line with previous work[6] and our results are also consistent with the study of Corbeels et al.[36] who showed that higher productive performance of CA systems in Africa can be expected when CA principles are implemented concomitantly in combination with herbicide application, especially for maize (Supplementary Fig. 2c1). However, we also need to note that part of the regional variability in the performance of CA and NT might be related to the diversity of farm characteristics in the different regions under consideration, in particular the level of mechanization and size of farm.

In addition to increasing crop yield, CA systems can potentially improve biodiversity, increase the soil organic matter and bring about positive environmental externalities such as reduced soil erosion, improved soil quality and enhanced carbon sequestration[2,3,37]. Moreover, CA could improve the resilience of cropping systems to climate change and increase the stability of crop yields[38,39]. Although several variants of CA systems may be associated with a high probability of yield loss in many regions, we also showed that, under future climate conditions and with good agricultural management practices, the relative productive performance of CA is expected to increase for several crop species. This is especially true for maize in tropical regions, which further strengthens the competitiveness of CA for this staple crop. Thus, our results support the idea that CA will be a relevant option for cropping systems in the future, capable of ensuring a long-term, sustainable agricultural production for some key cropping areas[40,41].

Online content

Any methods, additional references, Nature Research reporting summaries, source data, extended data, supplementary information, acknowledgements, peer review information; details of author contributions and competing interests; and statements of data and code availability are available at https://doi.org/10.1038/s41558-021-01075-w.

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References

1. Bisht, J. K, Meena, V. S, Mishra, P. K. & Pattanayak, A. (eds) *Conservation Agriculture: An Approach to Combat Climate Change in Indian Himalaya* (Springer, 2016).
2. Farooq, M. & Siddique, K. H. M. (eds) *Conservation Agriculture* (Springer, 2015).
3. Giller, K. E. et al. Beyond conservation agriculture. *Front. Plant Sci.* **6**, 870 (2015).
4. Jat, S. L. et al. Differential response from nitrogen sources with and without residue management under conservation agriculture on crop yields, water-use and economics in maize-based rotations. *Field Crops Res.* **236**, 96–110 (2019).
5. Steward, P. R. et al. The adaptive capacity of maize-based conservation agriculture systems to climate stress in tropical and subtropical environments: a meta-regression of yields. *Agric. Ecosyst. Environ.* **251**, 194–202 (2018).
6. Pittelkow, C. M. et al. When does no-till yield more? A global meta-analysis. *Field Crops Res.* **183**, 156–168 (2015).
7. *Conservation Agriculture* (FAO, 2020); http://www.fao.org/conservation-agriculture/en/
8. Pittelkow, C. M. et al. Productivity limits and potentials of the principles of conservation agriculture. *Nature* **517**, 365–368 (2015).
9. Nichols, V., Verhulst, N., Cox, R. & Govaerts, B. Weed dynamics and conservation agriculture principles: a review. *Field Crops Res.* **183**, 56–68 (2015).
10. Su, Y., Gabrielle, B. & Makowski, D. A global dataset for crop production under conventional tillage and no tillage practice. *figshare* https://doi.org/10.6084/m9.figshare.12155553 (2020).
11. Su, Y., Gabrielle, B. & Makowski, D. A global dataset for crop production under conventional tillage and no tillage systems. *Sci. Data* **8**, 33 (2020).
12. *University of Delaware Air Temperature & Precipitation* (NOAA/OAR/ESRL PSL, 2020); https://www.esrl.noaa.gov/psd/data/gridded/data.UDel_AirT_Precip.html
13. *CPC Global Daily Temperature* (NOAA/OAR/ESRL PSL, 2020); https://www.esrl.noaa.gov/psd/data/gridded/data.cpc.globaltemp.html
14. Martens, B. et al. GLEAM v3: satellite-based land evaporation and root-zone soil moisture. *Geosci. Model Dev.* **10**, 1903–1925 (2017).
15. Miralles, D. G. et al. Global land-surface evaporation estimated from satellite-based observations. *Hydrol. Earth Syst. Sci.* **15**, 453–469 (2011).
16. *Crop Calendar Dataset: netCDF 5 degree* (Univ. of Wisconsin-Madison, 2020); https://nelson.wisc.edu/sage/data-and-models/crop-calendar-dataset/netcdf0-5degree.php
17. Ho, T. K. Random decision forests. In *Proc. 3rd International Conference on Document Analysis and Recognition* 278–282 (IEEE, 1995).
18. Kottek, M., Grieser, J., Beck, C., Rudolf, B. & Rubel, F. World Map of the Köppen–Geiger climate classification updated. *Meteorol. Z.* **15**, 259–263 (2006).
19. Laborde, J. P., Wortmann, C. S., Blanco-Canqui, H., Baigorria, G. A. & Lindquist, J. L. Identifying the drivers and predicting the outcome of conservation agriculture globally. *Agric. Syst.* **177**, 102692 (2020).
20. Su, Z. et al. Effects of conservation tillage practices on winter wheat water-use efficiency and crop yield on the Loess Plateau, China. *Agric. Water Manag.* **87**, 307–314 (2007).
21. van Wie, J. B., Adam, J. C. & Ullman, J. L. Conservation tillage in dryland agriculture impacts watershed hydrology. *J. Hydrol.* **483**, 26–38 (2013).
22. Shukla, M. K., Lal, R. & Ebinger, M. Tillage effects on physical and hydrological properties of a typica argiaquoll in Central Ohio. *Soil Sci.* **168**, 802–811 (2003).
23. Shen, Y., McLaughlin, N., Zhang, X., Xu, M. & Liang, A. Effect of tillage and crop residue on soil temperature following planting for a Black soil in Northeast China. *Sci. Rep.* **8**, 4500 (2018).
24. Zuazo, V. H. D. & Pleguezuelo, C. R. R. Soil-erosion and runoff prevention by plant covers. A review. *Agron. Sustain. Dev.* **28**, 65–86 (2008).
25. Shaxson, F. & Barber, R. *Optimizing Soil Moisture for Plant Production: The Significance of Soil Porosity* (FAO, 2003).
26. Derpsch, R., Sidiras, N. & Roth, C. H. Results from studies made from 1977–1984 to control erosion by no-tillage techniques in Paraná, Brazil. *Soil Tillage Res.* **8**, 253–263 (1986).
27. TerAvest, D., Carpenter-Boggs, L., Thierfelder, C. & Reganold, J. P. Crop production and soil water management in conservation agriculture, no-till, and conventional tillage systems in Malawi. *Agric. Ecosyst. Environ.* **212**, 285–296 (2015).
28. Page, K. L., Dang, Y. P. & Dalal, R. C. The ability of conservation agriculture to conserve soil organic carbon and the subsequent impact on soil physical, chemical, and biological properties and yield. *Front. Sust. Food Syst.* **4**, 31 (2020).
29. Halvorson, A. D. et al. Spring wheat response to tillage and nitrogen fertilization in rotation with sunflower and winter wheat. *Agron. J.* **92**, 136–144 (2000).
30. Radford, B. J. & Thornton, C. M. Effects of 27 years of reduced tillage practices on soil properties and crop performance in the semi-arid subtropics of Australia. *Int. J. Energy Environ. Econ.* **19**, 565 (2011).
31. García-Palacios, P., Alarcón, M. R., Tenorio, J. L. & Moreno, S. S. Ecological intensification of agriculture in drylands. *J. Arid. Environ.* **167**, 101–105 (2019).
32. Scopel, E. et al. Conservation agriculture cropping systems in temperate and tropical conditions, performances and impacts. A review. *Agron. Sustain. Dev.* **33**, 113–130 (2013).
33. Thierfelder, C. & Wall, P. C. Investigating conservation agriculture (CA) systems in Zambia and Zimbabwe to mitigate future effects of climate change. *J. Crop Improve.* **24**, 113–121 (2010).
34. Lal, R. The role of residues management in sustainable agricultural systems. *J. Sustain. Agric.* **5**, 51–78 (1995).
35. Thierfelder, C. et al. Complementary practices supporting conservation agriculture in southern Africa. A review. *Agron. Sustain. Dev.* **38**, 16 (2018).
36. Corbeels, M., Naudin, K., Whitbread, A. M., Kühne, R. & Letourmy, P. Limits of conservation agriculture to overcome low crop yields in sub-Saharan Africa. *Nat. Food* **1**, 447–454 (2020).
37. Smith, P., Powlson, D. S., Glendining, M. J. & Smith, J. U. Preliminary estimates of the potential for carbon mitigation in European soils through no-till farming. *Glob. Change Biol.* **4**, 679–685 (1998).
38. Williams, A. et al. A regionally-adapted implementation of conservation agriculture delivers rapid improvements to soil properties associated with crop yield stability. *Sci. Rep.* **8**, 8467 (2018).
39. Kassam, A., Friedrich, T., Shaxson, F. & Pretty, J. The spread of conservation agriculture: justification, sustainability and uptake. *Int. J. Agric. Sustain.* **7**, 292–320 (2009).
40. Hobbs, P. R., Sayre, K. & Gupta, R. The role of conservation agriculture in sustainable agriculture. *Phil. Trans. R. Soc. B* **363**, 543–555 (2008).
41. Govaerts, B. et al. Conservation agriculture as a sustainable option for the central Mexican highlands. *Soil Tillage Res.* **103**, 222–230 (2009).

Methods

Data collection. The literature search was done in February 2020 using the following keywords 'conservation agriculture/ no-till/ no tillage/ zero tillage' and 'yield/ yield change' in the websites ScienceDirect and Science Citation Index (Web of Science). We also collected the papers cited in previous meta-analyses[5,6,8], supplementing them by the most recently published experimental studies. A total of 1,012 potentially relevant papers were identified by reviewing the title and abstract; these papers were then screened according to the procedure summarized in Supplementary Fig. 6. More details about this screening and selection procedure were presented in previous studies[11,42]. In the end, 422 papers were retained (published between 1983 to 2020). From these papers, we were able to extract 4,403 paired yield observations from NT and CT for eight major crop species, including 370 observations for barley (232 observations for spring barley and 138 for winter barley), 94 observations for cotton, 1,690 observations for maize, 195 observations for rice, 160 observations for sorghum, 583 observations for soybean, 61 observations for sunflower and 1,250 observations for wheat (1,041 observations for winter wheat and 209 observations for spring wheat) in 50 countries from 1980 to 2017 (Extended Data Fig. 4). We also retrieved from the papers information on crop type, year and location of the experiments and agricultural management activities for both NT and CT systems, including crop irrigation (yes versus no), the field fertilization (yes versus no) and the details of the type and amount of fertilizer used, integrated weed and pest control (yes versus no) and the type of herbicide and pesticide used, crop rotation (yes versus no) and details of crop sequence and information of cover crops, soil cover (yes versus no) and the details of residues retention from previous crops or cover crops. On the basis of this information, we were able to define CA as the combination of NT with soil cover and rotation and to distinguish this system from other variants (NT without soil cover and rotation, NT with rotation but without soil cover, NT with soil cover but without rotation). Additional data were extracted from several external databases, pertaining to crop growing season[16], soil texture[43] and climate factors such as precipitation (P)[12], minimum air temperature (T_{min})[13], average air temperature (T_{ave})[12], maximum air temperature (T_{max})[13] and potential evapotranspiration (E)[14,15] in the growing season[16] in the particular year of the experiment 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 × 0.5° longitude and, if the source data were in a finer spatial resolution, they were downscaled to the resolution of 0.5° latitude × 0.5° longitude.

Model training and cross-validation. The machine-learning algorithm random forest[17] was trained to analyse the yield ratios of NT versus 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, T_{min}, T_{ave}, T_{max} were defined as numerical inputs, while crop type, soil texture and agricultural management activities including crop irrigation, field fertilization, integrated weed and pest control, crop rotation and soil cover management were defined as categorical inputs. The model output was expressed as the probability of yield gain from NT versus CT. When training, each tree in a random forest learns from a random sample of the data points. The samples are drawn with replacement (bootstrapping). Only a subset of all the inputs is considered for splitting each node in each decision tree. Predictions are made by averaging the predictions of all decision trees[44]. The performance of the algorithm was assessed by estimating the area under the ROC curve by leave-one-out cross-validation. The procedure and results of cross-validation are presented in detail in Supplementary Fig. 7 and in ref. [42]. Since crop rotation, soil cover management and other agricultural management practices were included as model inputs, it is possible to map the probability of yield gain for CA (NT with crop rotation and soil cover) and several variants of this system (NT partly or not implemented with crop rotation and soil cover) versus CT. Maps were generated for all crop species at a spatial resolution of 0.5° latitude × 0.5° longitude.

Global projection. The fitted random forest model was used to estimate the probability of yield gain from CA system and their variants versus CT without crop rotation (−R) and without soil cover (−SC) for each grid cell located in cropping regions under current (2011–2020) and future (2051–2060) climate scenarios. This variant of CT was chosen as a baseline comparator because it prevails in the training dataset[10,11]. The monthly average values of the climatic variables (PB, T_{min}, T_{ave}, T_{max}) were calculated in each grid cell over the two time periods considered and then these data were used to calculate the climatic variables during the growing season on the basis of the crop calendar database[16] (assume no change in current and future scenario). All the climatic data in both current and future scenarios were obtained from four climate models: Gfdl-esm2m, Hadgem2-es, Ipsl-cm5a-lr and Miroc5 and four RCP scenarios: RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5. This results in 32 combinations: four climate models × four RCP scenarios × two periods. We mainly focused on the Ipsl-cm5a-lr model and RCP 4.5 scenario in the baseline simulations because of their importance and similar role in the protocol of ISIMIP2b project[45]. However, results from all combinations were analysed and shown in Extended Data Fig. 3. All the climatic data can be downloaded through the website of Lawrence Livermore National Laboratory[46].

We did not change the categorical inputs describing cropping practices between current and future scenarios. The global soil texture was set on the basis of the HWSD dataset[43]. To compare the performance across different cropping systems, we mapped the probability of yield gain and the change of yield gain probability under climate change with the systems of CA (+F+WD) versus CT–R–SC (+F+WD), CA (−F−WD) versus CT–R–SC (−F−WD), NT+R–SC (+F+WD) versus CT–R–SC (+F+WD), NT–R–SC (+F+WD) versus CT–R–SC (+F+WD), NT–R–SC (−F−WD) versus CT–R–SC (−F−WD), where +/−R indicated crop rotation set as yes/ no, +/−SC indicated soil cover set as yes/ no, +/− F indicated fertilization set as yes/ no and +/−WD indicated weed and pest control set as yes/ no. As for crop irrigation, it was set on the basis of the crop irrigation mask from MIRCA2000 dataset[47]. When more than 50% of the area in a grid cell was under rainfed conditions for a given crop in the MIRCA2000 database, this cell was then considered as non-irrigated for this crop and vice versa. See Supplementary Table 1 for the details of model settings. The model outputs were mapped at a spatial resolution of 0.5° latitude × 0.5° longitude on the basis of the MIRCA2000 crop mask database[47]. Accumulated area fractions under different levels of yield gain probability and different levels of probability change between current and future scenarios were computed at the global scale and in different climate regions.

Climate regions. The term 'global' indicated the global cropping region for each crop. Climate was classified according to the Köppen–Geiger classification[18] and its nomenclature (Supplementary Fig. 8). The term 'tropical climate' included the regions with the climate types Af, Am, As and Aw (ref. [18]). The term 'dry climate' included the regions with the climate types BWk, BWh, BSk and BSh (ref. [18]). The term 'temperate climate' included the regions with the climate types Cfa, Cfb, Cfc, Csa, Csb, Csc, Cwa, Cwb and Cwc (ref. [18]). The term 'continental climate' included the regions with the climate types Dfa, Dfb, Dfc, Dfd, Dsa, Dsb, Dsc, Dsd, Dwa, Dwb, Dwc and Dwd (ref. [18]).

Reporting Summary. Further information on research design is available in the Nature Research Reporting Summary linked to this article.

Data availability

The dataset[10] is made fully available and described in a data paper[11]. The dataset can be accessed using the following link: https://doi.org/10.6084/m9.figshare.12155553.

Code availability

All the R and MATLAB codes are available in figshare and can be accessed through the link https://doi.org/10.6084/m9.figshare.14427977 or on request from the corresponding author.

References

42. Su, Y., Gabrielle, B., Beillouin, D. & Makowski, D. High probability of yield gain through conservation agriculture in dry regions for major staple crops. *Sci. Rep.* **11**, 3344 (2021).
43. *Soil Texture Map* (Univ. of Tokyo, 2020); http://hydro.iis.u-tokyo.ac.jp/~sujan/research/gswp3/soil-texture-map.html
44. Breiman, L. Random Forests. *Mach. Learn.* **45**, 5–32 (2001).
45. Frieler, K. et al. Assessing the impacts of 1.5 °C global warming—simulation protocol of the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP2b). *Geosci. Model Dev.* **10**, 4321–4345 (2017).
46. *ESGF Project* (Lawrence Livermore National Laboratory, 2020); https://esgf-node.llnl.gov/projects/esgf-llnl/
47. Portmann, F. T., Siebert, S. & Döll, P. MIRCA2000-Global monthly irrigated and rainfed crop areas around the year 2000: a new high-resolution data set for agricultural and hydrological modeling. *Global Biogeochem. Cycles* **24**, GB1011 (2010).

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Author contributions

Y.S. wrote the main manuscript text and B.G. and D.M. modified it. Y.S., B.G. and D.M. worked together to prepare the figures and tables. Y.S. collected the data. Y.S., B.G. and D.M. designed and built the models to process the data. Y.S. worked on the model cross-validation. All authors reviewed the manuscripts.

Competing interests

The authors declare no competing interests.

Additional information

Extended data is available for this paper at https://doi.org/10.1038/s41558-021-01075-w.

Supplementary information The online version contains supplementary material available at https://doi.org/10.1038/s41558-021-01075-w.

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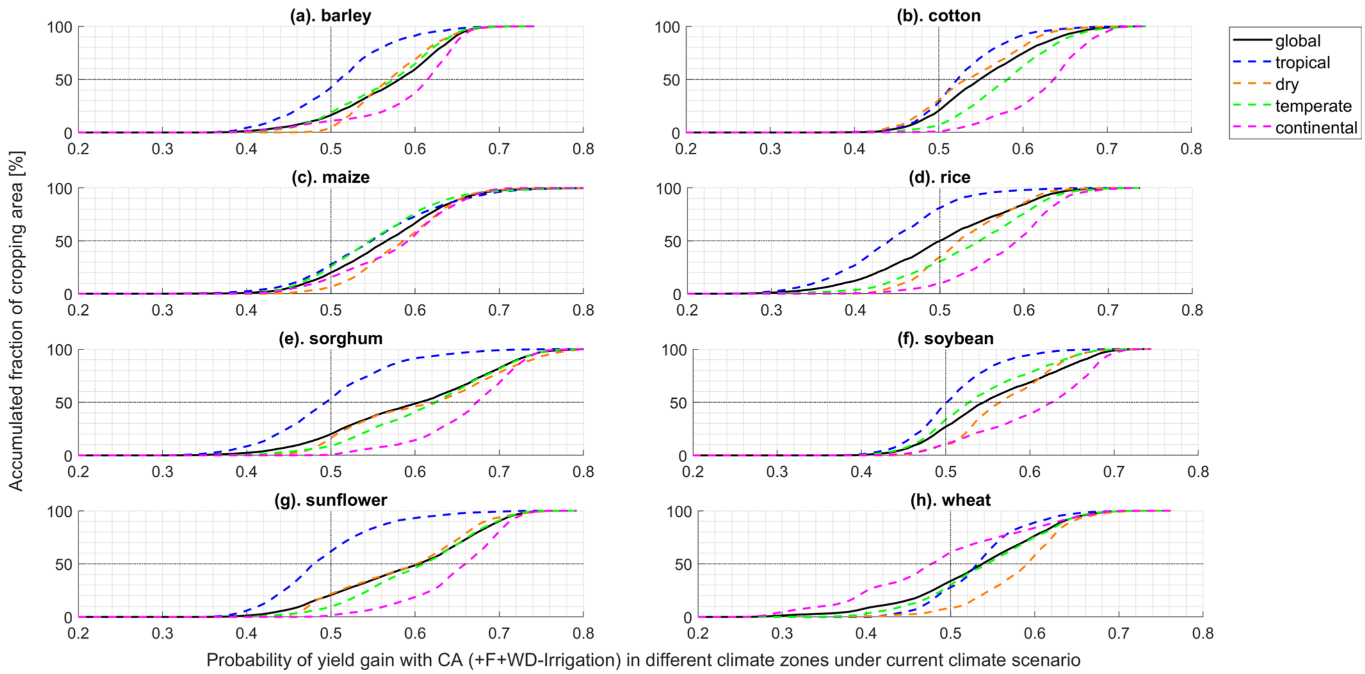
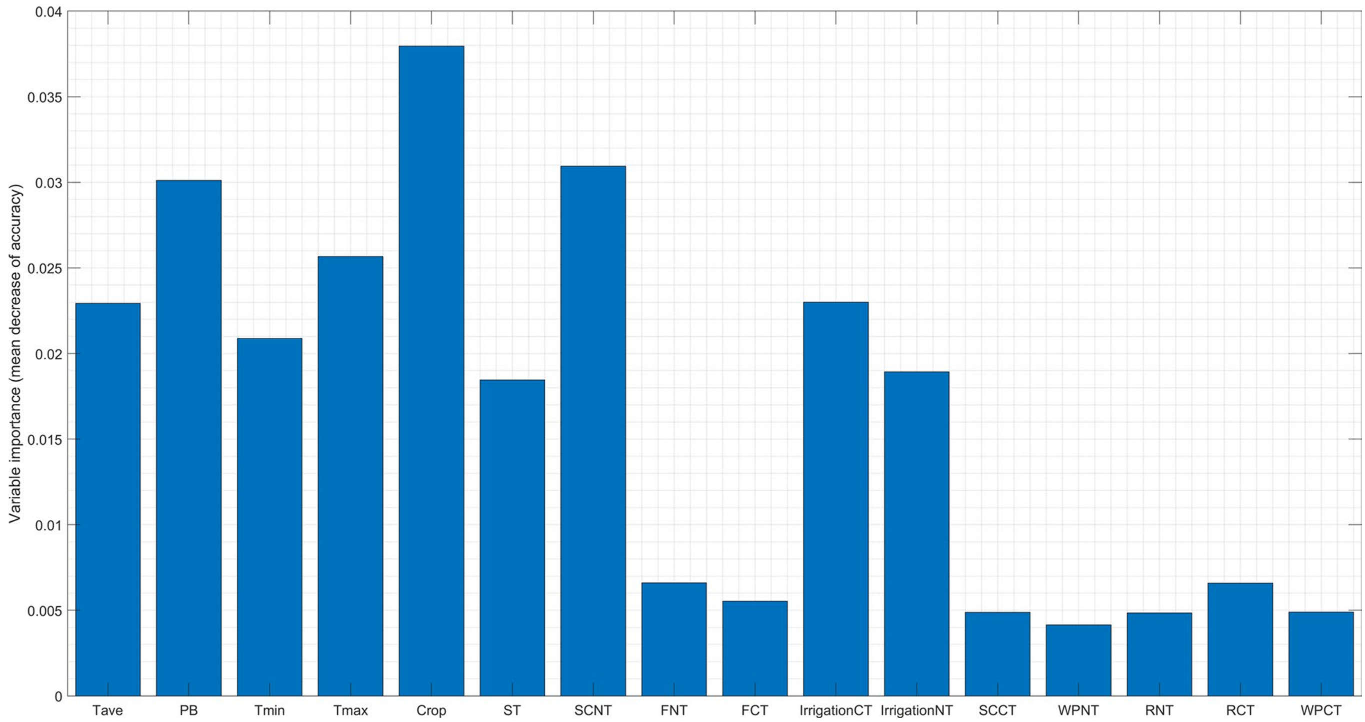
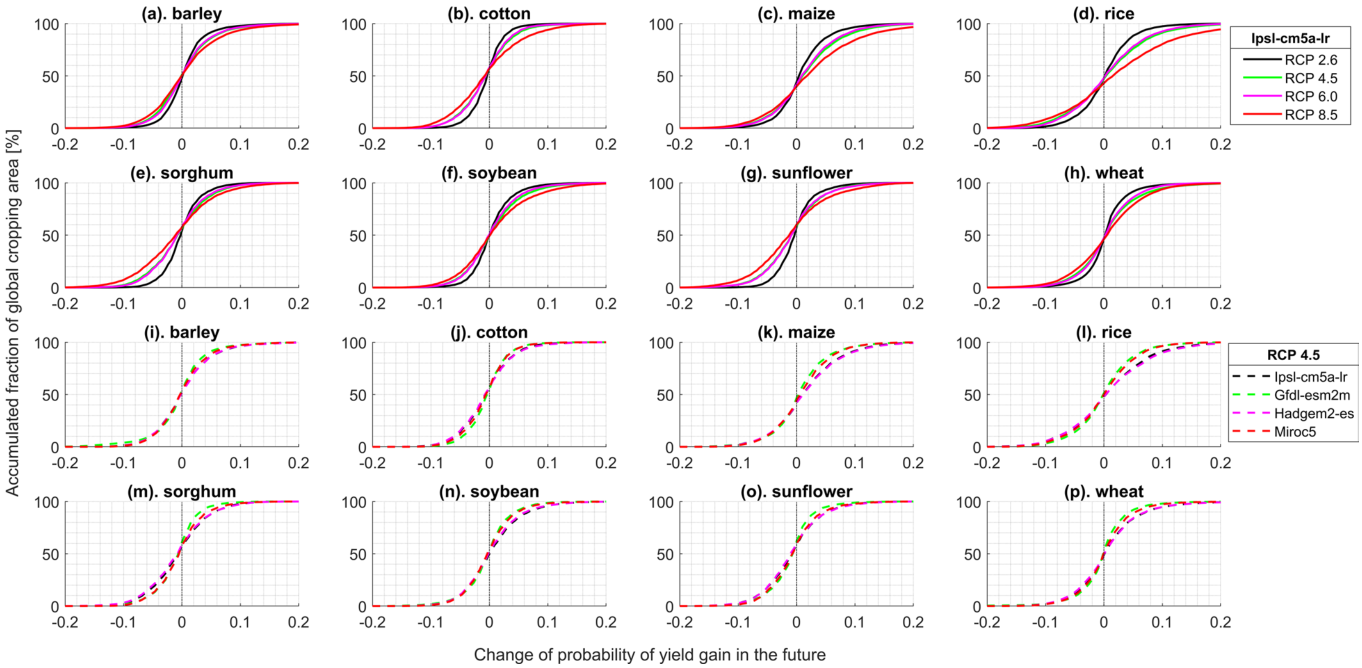


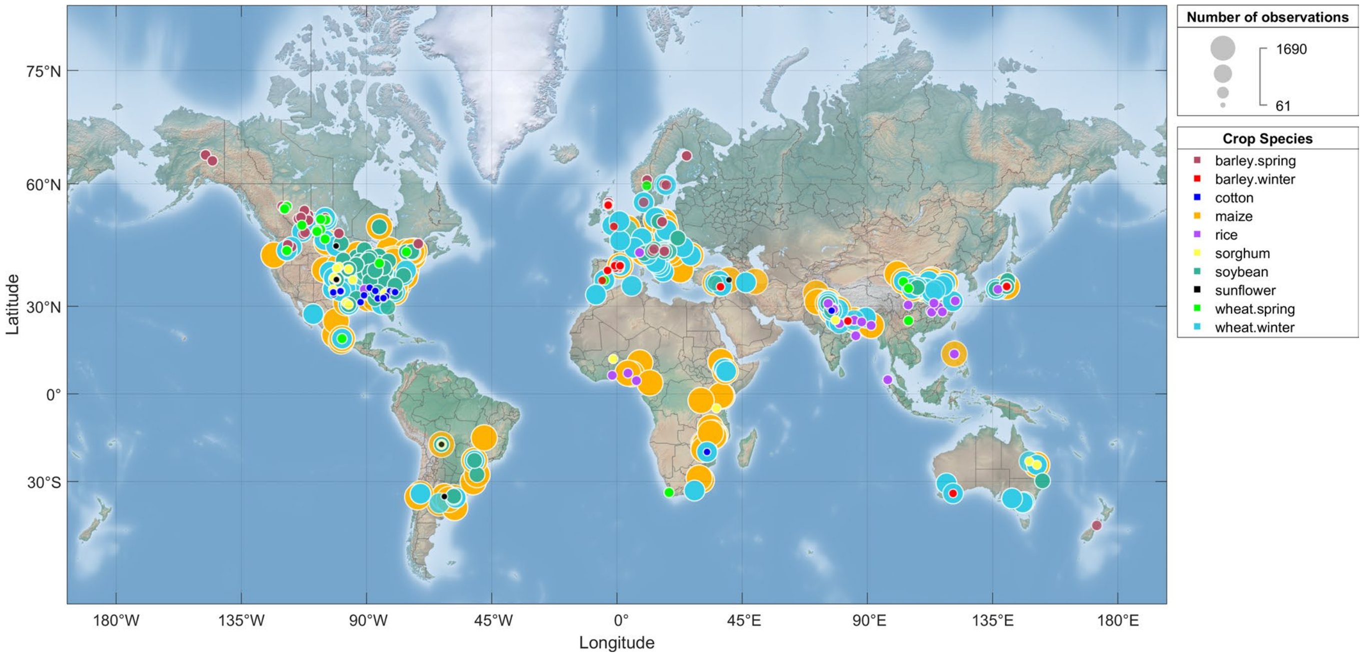
Extended Data Fig. 1 | Accumulated fraction of the cropping area as a function of the probability of yield gain under CA (+F+WD -Irrigation) versus CT–R–SC (+F+WD -Irrigation) systems in different climate regions. Accumulated fraction of the cropping area as a function of the probability of yield gain under CA (+F+WD – Irrigation) versus CT–R–SC with fertilization (+F) and weed and pest control (+WD) without irrigation (–Irrigation) for eight major crops (a–h) and different climate zones. The results are based on the average climate conditions over 2021–2020 simulated by the Ipsl-cm5a-lr climate model and RCP 4.5 scenario.



Extended Data Fig. 2 | Relative importance ranking of the model inputs. The importance was defined by the mean decrease in accuracy in the 'cforest' model. Where 'PB' indicates precipitation balance over crop growing season; 'Tmax' indicates maximum air temperature over crop growing season;'Tave' indicates average air temperature over crop growing season; 'Tmin' indicates minimum air temperature over crop growing season; 'Crop' indicates the crop species;'ST' indicates soil texture; 'SCNT' indicates soil cover management under the variants of no tillage systems; 'SCCT' indicates soil cover management under CT systems; 'RNT' indicates crop rotation management under the variants of no tillage systems; 'RCT' indicates crop rotation management under CT systems; 'FNT' indicates management of crop fertilization under the variants of no tillage systems; 'FCT' indicates crop management of crop fertilization under CT systems; 'WDNT' indicates management of weed and pest control under the variants of no tillage systems; 'WDCT' indicates crop management of weed and pest control under CT systems.



Extended Data Fig. 3 | The accumulated fraction of the cropping area in different level of change on the probability of yield gain under CA (+F+WD) versus CT-R-SC (+F+WD) under different crops, climate models and RCP scenarios. The accumulated fraction of the cropping area in different level of change on the probability of yield gain under CA (+F+WD) versus CT-R-SC (+F+WD) for different crops, climate models and RCP scenarios. The results are based on the average climate data in different RCP scenarios (RCP 2.6, RCP 4.5, RCP 6.0, RCP 8.5) in Ipsl-cm5a-lr model, and RCP 4.5 scenario in different climate models (Ipsl-cm5a-lr, Gfdl-esm2m, Hadgem2-es, Miroc5) for both current (2021–2020) and future (2051–2060) scenarios.



Extended Data Fig. 4 | Distributions of experiment site for each crop. This map and the corresponding dataset are presented in ref. 11, 42. This figure was generated by MATLAB R2020a (Version 9.8.0.1451342, https://fr.mathworks.com/products/matlab.html). In this meta-dataset (ref. [11]), 4403 paired yield observations were extracted from NT and CT for 8 major crop species, including 370 observations for barley (232 observations for spring barley and 138 for winter barley), 94 observations for cotton, 1690 observations for maize, 195 observation for rice, 160 observations for sorghum, 583 observations for soybean, 61 observations for sunflower, 1250 observations for wheat (1041 observations for winter wheat and 209 observations for spring wheat) in 50 countries from 1980 to 2017.

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☒	☐	For Bayesian analysis, information on the choice of priors and Markov chain Monte Carlo settings
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Data analysis	R language, version 4.04; R studio, version 1.2.1335; MATLAB R2020a, version 9.8.0.1538580

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All studies must disclose on these points even when the disclosure is negative.

Study description	The data come from the systematic review of crop yield in conservation agriculture vs. conventional tillage system, the details is described in our data paper, Su, Y., Gabrielle, B. & Makowski, D. A global dataset for crop production under conventional tillage and no tillage systems. Sci Data 8, 33 (2021).
Research sample	The dataset includes the results extracted from 413 papers, 4403 paired yield observations from NT and CT for 8 major crop species, including 370 observations for barley (232 observations for spring barley and 138 for winter barley), 94 observations for cotton, 1690 observations for maize, 195 observation for rice, 160 observations for sorghum, 583 observations for soybean, 61 observations for sunflower, 1250 observations for wheat (1041 observations for winter wheat and 209 observations for spring wheat) in 50 countries from 1980 to 2017.
Sampling strategy	The procedure to data screening was presented in detail in our data paper, Su, Y., Gabrielle, B. & Makowski, D. A global dataset for crop production under conventional tillage and no tillage systems. Sci Data 8, 33 (2021). Papers not reporting yield data for CT and NT systems were excluded, as well as papers reporting experiments on reduced tillage (RT) systems. Papers reporting only mean yield data across different years or sites were also excluded. We then checked whether information on fertilization, weed and pest control, crop irrigation, crop rotation and crop residue management were reported for both CT and NT practices.
Data collection	The data collection procedure was presented in detail in our data paper, Su, Y., Gabrielle, B. & Makowski, D. A global dataset for crop production under conventional tillage and no tillage systems. Sci Data 8, 33 (2021). 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', 'Science Citation Index (web of science)'. 4403 paired yield observations from NT and CT for 8 major crop species were collected manually from the collected papers.
Timing and spatial scale	Time scale: from 1980 to 2017; Spatial scale: global
Data exclusions	The procedure to data exclusion was presented in detail in the data paper, Su, Y., Gabrielle, B. & Makowski, D. A global dataset for crop production under conventional tillage and no tillage systems. Sci Data 8, 33 (2021). When the experiment's climate and soil data are not available in the external datasets, it was removed from the dataset.
Reproducibility	The dataset is fully available online, which can be accessed through the link: https://doi.org/10.6084/m9.figshare.12155553
Randomization	Not relevant here as we did not conduct new experiment.
Blinding	Not relevant here as we did not conduct new experiment.

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☒	☐ Human research participants
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