Authors' responses on reviewers' comments

esd-2019-8: A multi-model analysis of teleconnected crop yield variability in a range of cropping systems

Matias Heino, Joseph H. A. Guillaume, Christoph Müller, Toshichika Iizumi, and Matti Kummu

Note: Includes the response to both reviewers

We thank the editor and the reviewer for their careful evaluation of our manuscript and their constructive comments that helped us to improve the manuscript considerably. We have taken all the comments carefully into consideration when revising the paper. Please find our detailed responses to the review comments below. The main revisions include: 1) Assessing the sensitivity of crop yields to these oscillations by using a multivariate ridge regression framework, which controls for the co-variability of the oscillations; 2) Including an assessment about growing season weather teleconnections, and reflecting on how they relate to our main results; 3) Re-defining the allocation of annual growing seasons, so that the understanding of the teleconnections is better reflected in the analyses.

Reviewer

R1.1.: The authors use a suite of historical global gridded crop simulations from the AgMIP ensemble to examine the influence of natural climate oscillations on correlated crop yield impacts. Consistent with observed yield analyses, they find that ENSO variability can simultaneously affect nearly 50% of harvested areas for certain crops, while other modes of variability affect smaller areas but still have significant impacts. The authors suggest that this could help forecast climate shocks on the food system. Using additional simulations, they show that irrigation reduces the sensitivity to such climate variability but fertilizer application doesn't have a significant influence on reducing the climate sensitivity on these crops.

The study is an extension of work that has already been done by the authors on observed yields. While these simulations are helpful to isolate the role of climate variability and test scenarios of irrigation and fertilizer application, they do not provide a mechanistic explanation of the impacts or comparisons with the magnitude and extent of observed impacts. Although, I think this is a worthwhile study since crop models present some important tools to study the impacts of climate variability and management decisions, I have some major concerns about the methods and design of the study, which will affect the main conclusions. Before considering the merit of this manuscript for publication, I believe these following concerns need to be addressed.

A1.1: Firstly, we want to thank the reviewer for the overall positive view of our study. We agree with the reviewer that using simulated crop yield data can provide important insights about climate impacts on crop productivity, while allowing to test for potential management options. However, we agree that the statistical method used does not allow mechanistic explanation of impacts. This is outside of our scope in this study.

As the reviewer notes, overall results are consistent with previous studies. Although, we relate our claims and results to existing knowledge throughout the text, detailed comparison with observed impacts is not performed – this is a highly complex task given the uncertainties and confounding variables in the reported crop statistics (e.g. technological change, management decisions, pest outbreaks, multiple cropping, crop rotations) as well as modelled data. In the following sections we explain how we have addressed the issues raised by the reviewer.

R1.2.: The three indices used include ENSO, IOD and NAO. All 4 crops studied here have almost identical sensitivities to ENSO and IOD, with some differences likely due to slightly different time periods used. I have a strong suspicion that this is because the ENSO and IOD indices have strong co-variability. Positive IOD's tend to develop during the development of positive ENSO phases (e.g Zhang et al., 2015, Stuecker et al. 2017). IOD's in the Fall are often followed by the peak of El Nino events in the winter. Based on how the time periods of the analyses are defined, this analysis is likely capturing the effect of El Ninos NOT IOD's.

A1.2.: We want to thank the reviewer for pointing out that the results for IOD are potentially affected by its co-variability with ENSO. Therefore, instead of calculating the direct relationship between the IOD index and crop yields (as done in original submission), we now calculate the sensitivity of crop yield to IOD by controlling for ENSO as well as NAO by using multivariate ridge regression. The ridge regression framework was selected because it allows the explanatory variables (here oscillation indices) to correlate amongst each other.

After conducting the analysis with the updated method, for ENSO and NAO the patterns stayed relatively similar (Figure 1, some changes occurred also due to the changes made to the allocation of growing seasons), while for IOD the changes were larger, consistent with the reviewer's hypothesis that the previous IOD results were capturing the effect of ENSO. For the IOD some changes occurred e.g. in the Middle East and the Americas, however, the most important teleconnections (e.g. in Australia) still remained the same.

R1.3.: Relatedly, there needs to be some mechanistic explanation for how the NAO and IOD events influence yields in remote areas where they do not have strong (if any) climate teleconnections (reference Figure 1). For example, what is driving the yield sensitivity of crops in North America during IODs or in southern Africa during NAO events? I would recommend showing the underlying temperature and precipitation variability in response to each ENSO, IOD and NAO phases to support these findings.

A1.3.: We agree with the reviewer that it is important to carefully reflect our results against existing understanding of the climate oscillations and their teleconnections. Hence, we have assessed how growing season temperature and soil moisture anomalies vary in relation to the oscillations included here (Figs S2-S3). In the main text, across Section 3.2, we then reflect on how the patterns found for weather variability relate to our main results.

R1.4.: (Page 6, Section 2.3) In defining the oscillation specific harvest years, the evolution of the oscillations and their teleconnections in not correctly accounted for. The harvest years, in some places, cover multiple growing seasons. For example, IOD climate teleconnections do not typically last beyond the Fall season in which the IOD's occur into the following year's growing season, so including those subsequent seasons will provide spurious relationships. Similarly, El Nino's affect certain areas of the tropics such as South Asia strongly during the developing phase (Kumar et al., 2006). By defining the harvest year as starting on 1 December, these important connections are missed. Further, by extending them to the following growing season, when the impacts don't occur or as is stated in the manuscript, phase changes might occur, these sensitivities are likely to be spurious. For ENSO, it might make sense to define the harvest year from the growing season of the year it starts to develop to the start of the following year's growing season. For IOD and NAO, which are shorter lived, it might be more suitable to restrict harvest years to seasons when their impacts are known.

A1.4.: In general, it is difficult to select the most appropriate harvest years for the oscillations, as different areas and crops have varying growing periods, which are impacted differently by the studied oscillations. For example, if the ENSO specific growing season was defined to begin at the beginning of the year, it could mask out some important maize and soybean teleconnections in northern South America, where, according to the models, maize and soybean planting occurs around January. Further, it should be noted that in GGCMI the models simulated only a single growing season annually.
The only way to convincingly resolve this issue is to fully unpick the mechanisms involved, including capturing temporal relationships between: 1) oscillation indices and weather, 2) climate and growing conditions, e.g. soil water availability, 3) growing conditions and yield, including variability of weather during the season potentially induced by the teleconnection. This is outside the scope of this paper.

However, we have re-defined the growing periods related to these oscillations so that the growing period for all these studied oscillations start in May and goes until the end of the following April, as this time period should capture the most important known teleconnections, e.g. in Australia, Asia and South America. It should be noted that due to these changes in the growing periods, some differences in the sensitivity direction occurred in the results for ENSO (Fig. 1), as the growing periods of e.g. soy and maize in the U.S. now fall in the period before ENSO would peak, while in the previous analyses their growing periods would've been after the ENSO peak.

R1.5.: Page 6, Section 2.2) Regarding the El Nino index used, I would recommend using more commonly used metrics such as the Nino 3.4 index or at least test the sensitivity of your results to the Nino 3.4 Index, which is typically used to identify climate teleconnections.

A1.5.: We have now conducted the same analysis using also the Niño 3.4 index (Figure S6), and the main results remain the same with this index as well. This helped increase the credibility of our results on ENSO impacts further. Thank you for the suggestion.

R1.6.: I realize that the models used here have been evaluated in a different paper. However, it would be useful to include an evaluation of the models in the supplement for metrics relevant here. For instance, how does each model capture observed yield various across global harvested areas. While the authors state that no model is obviously superior, they do not state whether any of them are capable of simulating observed yields.

A1.6.: We have now added a table (Table S1) adopted from Muller et al. (2017), which shows how well the simulated crop yields match reported yields from FAOSTAT at global level.

R1.7.: (Page 7, Section 2.4) The authors have used a linear regression model here. As far as I can tell, each mode is tested separately. However, given that they are related, I would think it would be more appropriate to have a multiple regression framework to isolate their individual influences.

A1.7.: Indeed, we agree that it is a good idea to use a multiple regression framework to account for the co-variability between the oscillations. Therefore, as described above (see reply to R1.2), we now use ridge regression to assess how the crop yields are impacted by these oscillations.

R1.8.: I am a bit flabbergasted at the inclusion of 24 maps in one figure (!!!). I would strongly recommend either splitting this plot by index or phase or crop. 24 is too many and I imagine others, like me, might have difficulty processing the information in Figure 2. Instead of a separate figure for agreement, it would be helpful to show agreement on the maps in Figure 1 and 2, especially after splitting Figure 2. These changes will enhance the clarity of the figures and help decipher areas of model (dis)agreement more clearly.

A1.8.: We appreciate that the number of maps can be overwhelming at first glance. The use of "small multiples" is, however, common in visualisation as an effective way of providing a quick overview so that large quantities of data can be compared. In this case, the figure allows comparison of spatial patterns across crops, phases and indices. Splitting by either of these would then hamper comparison. At the same time, the casual reader does not need to identify parameters by themselves – the patterns are discussed in text. To clarify this point, the caption now adds: "Patterns are discussed in Sections 3.1 and 3.2."

Rather than modifying Figure 3, we have tried to clarify its role in the paper. The original caption indicated that it shows “agreement” between models and methods, which falsely gave the impression that it should be primarily read with Figure 1 and 2. On the contrary, it is intended as a robust summary of locations where indices and yields are related. The caption now reads: “Summary of relationship between ENSO, IOD, and NAO and crop yields across models and methods”

R1.9.: Page 14, Lines 15-20, It is a bit misleading to say that the sensitivity of crops to climate variability, increases with fertilizer application, given the discussion in these lines. If crop yields are improved during suitable climate conditions, that is a net positive, and it would be useful to have a metric to capture that improvement rather than suggest a negative effect of adding fertilizers.

A1.9.: We apologize that we have not clearly communicated our results. Indeed, we don’t imply that fertilizers are not useful in increasing crop yields, but merely that they may not be effective in mitigating weather related impacts; i.e. we were only discussing potential reasons, why these the numbers come out this way. We now mention this in the main text: “Note that this does not mean fertiliser fails to improve crop yields – only that it does not lead to more stable yields in the face of weather variability” (Page 14, Lines 23-24).

R1.10.: In Figure 4, the sensitivity of all crops is higher in the fully irrigated scenarios vs rainfed, based on Column 1. How does this suggest that irrigation reduces the sensitivity? This is likely just my confusion because of the way the information is presented in Figure 4. In Figure 4, is column 1, the difference in sensitivities of yield variability in the irrigation scenario – the rainfed scenario or vice versa? Does a positive difference suggest higher sensitivity in the irrigation scenario relative to the rainfed scenario?

A1.10.: We have now clarified the figure so that the panel titles indicate that the sensitivity differences are calculated as change in sensitivity relative to a baseline, which is the Fully irrigated scenario for the 1st panel, and the Actual scenario for the four other panels.

R1.11.: The conclusions will change if the analysis is changed to include the suggestions above. The discussion and conclusions sections will need to be edited accordingly.

A1.11.: We have modified the Discussion and Conclusions sections to reflect our revised results. However, as our main results did not change significantly, no large changes were needed in these sections.

R1.12.: I encourage the author to include a discussion of the existing literature on the covariability of IOD/NAO and EL Nino indices.

A1.12.: We have now included a paragraph discussing the covariability between IOD (as well as briefly NAO) and ENSO in the Discussion.

R1.13.: Page 2 Line 16, what is the reference for IOD events being forecast months in advance?

A1.13.: Two studies by Luo et al. (2005 & 2008) show successful prediction of three IOD events (1994, 2006 and 2007) with seasonal lead time. However, as these results don’t show that the status of IOD can be predicted at all times, the sentence was rephrased: “As the phase and development of ENSO, IOD and NAO can potentially be forecasted from several months (IOD, NAO (Luo et al. 2008, Scaife et al. 2014)) up to one year (ENSO (Luo et al., 2005, Ludescher et al. 2014)) in advance, –“ (Page 2, Lines 17-18).

R1.14.: Page 5 Line 1, what are the default model assumptions?

A1.14.: The default model configurations are based on the management and technology assumptions typically used by the modelling groups for historical simulations. Hence, for the default configuration the GGCMI coordinators allowed the modelling teams to define their own assumptions for setting up the models. This is now more explicitly mentioned in the text explained: “To account for varying assumptions of growing season and fertilizer use, in GGCMI, model simulations were conducted for three configurations: standard model assumptions (default), harmonized growing season and nutrient input (fullharm), and harmonized growing season with no nutrient limitation (harm-suffN). For the default configuration each modelling group were instructed to use their own model assumptions” (Page 4 Line 6 - Page 5 Line 3).

R1.15.: Page 5, Line 3, how are literature-based values different from default assumptions?

A1.15.: For the harmonized configurations the growing season and assumptions about fertilizer use are fixed (based on reported patterns from literature) among the models, while for the default configuration the modelling teams were allowed to use their own normal assumptions, which can be dynamic (e.g. planting dates can change depending on pre-season weather condition).

R1.16.: Page 7, Line 14, Where does the sample size number N=216 – 297 come from? Is that 12 models * number of simulation years somehow?

A1.16.: This is correct. The sample used for the regression is such that the crop yield time series of all the models is used for fitting the regression. This is now been more explicitly explained: “For the main analysis (actual scenario)), the regression was calculated for each FPU separately using crop yield anomaly time series from all GGCMs that simulate the crop in question with the AgMERRA climate input (N=216-297, depending on crop). Hence, we utilize the crop yield time series of all the models in fitting the regression.” (Page 7, Lines 15-17).

R1.17.: Section 2.5, What is the sample size for the comparison of the strong phases of each climate mode?

A1.17.: The strong negative and positive phases were defined based on the 25% and 75% percentiles of the indices. Thus, sample sizes were 54-74, depending on the crop in question. This is now explicitly mentioned in the revised text: “Strongly negative (positive) phases of the oscillations were defined as the years when the respective oscillation index was smaller (larger) than the 25th (75th) percentile of all yearly index values ($N_{anomaly}$ = 54-74, depending on crop)” (Page 8, Lines 8-10).

R1.18.: Page 10, first para, it would be useful to define the regions referred to in the discussion. For instance, I do not see wheat yield increases in “eastern South Asia” in the Fig. 1 as is suggested here.

A1.18.: We have now added a map about the regions we refer to in the text (Figure S1).

R1.19.: Page 14, The result that irrigation reduces sensitivity of different crops makes sense. It would be helpful to have a metric that captures the relative areas of "actual" irrigation to explain the differences in sensitivity of different crops.

A1.19.: The aim of this analysis was to look into the potential for changes in agricultural inputs, from the current baseline, to change the sensitivity of crop yields to these oscillations. Therefore, the current management conditions do impact the numbers obtained. We have included information about the current extent of irrigated areas to inform the reader that they do indeed affect the results: "This ranking is expected, as the majority of rice harvested areas are irrigated (62% globally) and soybean has the smallest irrigated area share of these four crops (8%), while maize (21%) and wheat (31%) fall in between (Portmann et al. 2010)" (Page 14, Lines 8-10).

R1.20.: Figure 4, Please edit this figure for clarity. I would recommend either including boxes around each panel or lines to separate them. Also, please provide complete panel titles for the right 3 columns. Is this "actual - fully irrigated" scenarios?

A1.20.: We apologize that the figure was not clearly set up, and thank for the suggestions made to improve the figure. We have now divided the panels using shading, included the titles for all the panels, as well as updated the panel titles to better reflect the analyses conducted.

R1.21.: In section 3, please refer to the specific panels in figure 4 in the discussion. I don't know which panel is being referred to the discussion, especially given the incomplete panel titles. I would also recommend doing this for other figures as much as possible.

A1.21.: We have now included more specific references to Figure 4, when discussing its results.

R1.22.: References:

Kumar, K. Krishna, B. Rajagopalan, M. Hoerling, G. Bates, M. Cane, 2006: Unraveling the Mystery of Indian Monsoon Failure During El Niño. Science, 314, 115-119.
Zhang, W., Wang, Y., Jin, F.âˇARˇ F., Stuecker, M. F., and Turner, A. G. (2015), Impact of different El Niño types on the El Niño/IOD relationship, Geophys. Res. Lett., 42, 8570– 8576, doi:10.1002/2015GL065703.

Stuecker, M. F., Timmermann, A., Jin, F.âˇARˇ F., Chikamoto, Y., Zhang, W., Wittenberg, A. T., Widiasih, E., andZhao, S. (2017), Revisiting ENSO/Indian Ocean Dipole phase relationships, Geophys. Res. Lett., 44, 2481– 2492, doi:10.1002/2016GL072308.

A1.22.: Thank you for directing us to these references. The references used in our replies, are listed below:

Müller, C., Elliott, J., Chryssanthacopoulos, J., Arneth, A., Balkovic, J., Ciais, P., Deryng, D., Folberth, C., Glotter, M., Hoek, S., Iizumi, T., Izaurralde, R. C., Jones, C., Khabarov, N., Lawrence, P., Liu, W., Olin, S., Pugh, T. A. M., Ray, D. K., Reddy, A., Rosenzweig, C., Ruane, A. C., Sakurai, G., Schmid, E., Skalsky, R., Song, C. X., Wang, X., De Wit, A. and Yang, H.: Global gridded crop model evaluation: Benchmarking, skills, deficiencies and implications, Geoscientific Model Dev., 10, 1403-1422, 10.5194/gmd-10-1403-2017, 2017.

Luo, J., Masson, S., Behera, S., Shingu, S. and Yamagata T.; Seasonal climate predictability in a coupled OAGCM using a different approach for ensemble forecasts, J. Climate, 18, 4474–4497, 2005.
Luo, J., Behera, S., Masumoto, Y., Sakuma, H. and Yamagata, T.: Successful prediction of the consecutive IOD in 2006 and 2007, Geophys. Res. Lett., 35, 2008.

Editor

R2.1.: This manuscript describes a regression analysis that seeks to identify the global spatial response of modeled crop yields to global teleconnection pattern index variations. The ability of the authors' analysis to quantify the role of irrigation in damping the oscillations of crop yield due to climate variability seems potentially important.

A2.1.: Firstly, we want to thank the editor for the overall positive view of our study. We agree with the editor that the data used in this study provides important insights into the role of irrigation in damping climate impacts on crop productivity.

R2.2.: However, the results show some surprisingly strong responses in areas far afield from the action centers of some of the teleconnection patterns. For example, a strong response in the yield of maize to the Indian Ocean Dipole is observed along the US-Canadian border, while a strong response in the yield of maize and soybeans to the North America Oscillation is observed in Southeastern Australia. These are surprising, since I can't find any evidence of a significant relationship between the IOD and sensible weather in North America, or between the NAO and sensible weather in Australia in global maps of these teleconnection patterns. It seems likely that these results are spurious, an accidental result of the large number of regions being modeled.

A2.2.: The editor is correct that due to the large number of areas being modelled, some false positives for our statistical tests are expected. However, we don't make any conclusions or recommendations based on our analysis alone, but reflect on how our results relate to the current knowledge before drawing conclusions.
Also, in addition to analyzing how crop yields vary with these oscillations, we have now included analyses about the sensitivity (using multivariate ridge regression) of temperature and soil moisture anomalies to these oscillations (Figure S2-S3). Based on these results, there seems to be a statistical relationship between IOD and weather in North America (see also Fig. 21 in Saji and Yamagata 2003) as well as a small influence of NAO in temperature conditions in Australia.

R2.3.: Before recommending this work for publication in Earth System Dynamics, I would like to see the a deeper exploration of the reliability of the relationships displayed. For example, it would be good see some scatterplots of the index values versus more directly relevant meteorological factors in each region (growing season length or precipitation) and of these factors versus yield, as well as between yield and index values, to get a sense of the predictive power of the relationships.

A2.3.: We agree with the editor that it is important to analyse the reliability of our results, and therefore already in the original submission, we included a relatively thorough analysis about the uncertainty of our results related to the gridded crop model ensemble used here (especially Figure 3).

As described above, we have now included an assessment about how soil moisture and temperature variability is related to these oscillations. Further, as the analysis includes over 500 spatial units, instead of providing scatter plots about the relationships, we provide the R^2 values for the regression results (Figure S13), which show that e.g. in Australia a substantial proportion of crop yield variability can be explained with the oscillations studied here. More extensive exploration of relationships with directly relevant meteorological factors is out of scope, as it risks giving the reader the impression that we understand the mechanisms involved better than we actually do.

R2.4.: Some other simple statistical tests would also be helpful. It would be good to see the whether the patterns of response of yield to teleconnection pattern presented in figures 1 and 2 are consistent when the timeseries are split into two parts (first half and second half).

A2.4.: We want to thank the editor for the suggestion. However, the statistical significance of the sensitivity values is already assessed by bootstrapping, which means that, for each spatial unit, we have calculated the regression for 1000 sub-samples of the crop yield data (explained in Page 7, Lines 20-22). This is a more thorough alternative to split-sample testing, and we therefore expect to find statistically significant sensitivity values in the same areas even if the time series is split in half.

R2.5.: Finally, the authors should discuss at greater length the relative predictability of the various teleconnection patterns and how that convolves with level of uncertainty in the unlagged annual relationships presented here. If the NAO can only be predicted a few months in advance, what remaining skill is available for forecasting of the NAO's associated crop yield variability in advance of the harvest? It's one thing to note that if a strong NAO will be present, crop yields in some parts of the world will be a few percent above normal, but how much knowledge of crop yield anomalies is left if we only know that there's a 20% higher than normal chance of a strong NAO index averaged over next growing season?

A2.5.: We fully agree that there is a long way to go before reliable forecasting is possible. This study only provides background knowledge on the (possible) existence of relationships. We have added a paragraph discussing the usefulness and limitations of our results in mitigating climate impacts on crop yields and society. In the paragraph we e.g. state that: "In Australia, there is significant potential to utilize the information of IOD along with ENSO, to understand crop yield fluctuations, as they can explain a large proportion of local crop yield variability (Fig. S13, Yuan and Yamagata 2015). -- However, the quality of predictions of this type would naturally depend on the skill of the climate forecasts as well as the strength of the teleconnection. This study only provides a first assessment of correlations, and further work is needed before reliable forecasts can be provided. "(page 16, Lines 10-16).

References:

Saji, N. H. and Yamagata, T.: Possible impacts of Indian Ocean dipole mode events on global climate, Climate Research, 25, 151-169, 2003.

Yuan, C. and Yamagata, T.: Impacts of IOD, ENSO and ENSO Modoki on the Australian winter wheat yields in recent decades, Scientific reports, 5, 2015.

A multi-model analysis of teleconnected crop yield variability in a range of cropping systems

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Abstract. Climate oscillations are periodically fluctuating oceanic and atmospheric phenomena, which are related to variations in weather patterns and crop yields worldwide. In terms of crop production, the most widespread impacts have been observed for the El Niño Southern Oscillation (ENSO), which has been found to impact crop yields in all continents that produce crops, while two other climate oscillations - the Indian Ocean Dipole (IOD) and the North Atlantic Oscillation (NAO) - have been shown to impact crop production especially in Australia and Europe, respectively. In this study, we analyse the impacts of ENSO, IOD and NAO on the growing conditions of maize, rice, soybean and wheat at the global scale, by utilizing crop yield data from an ensemble of global gridded crop models simulated for a range of crop management scenarios. Our results show that, while accounting for their potential co-variation, climate oscillations are correlated with simulated crop yield variability ~~is correlated to climate oscillations~~ to a wide extent (~~up to almost~~ half of all maize and wheat harvested areas for ENSO) and in several important crop producing areas, e.g. in North America (ENSO, wheat), Australia (IOD & ENSO, wheat) and northern South America (ENSO, soybean). Further, our analyses show that higher sensitivity to these oscillations can be observed for rainfed, and fully fertilized scenarios, while the sensitivity tends to be lower if crops were to be~~are~~ fully irrigated. Since, the development of ENSO, IOD and NAO can potentially be ~~reliably~~ forecasted well in advance, a better understanding about the relationship between crop production and these climate oscillations can improve the resilience of the global food system to climate related shocks.

1 Introduction

Climate oscillations are periodically fluctuating oceanic and atmospheric phenomena, and they have been shown to impact hydroclimatological conditions (Dai et al. 1998, Hurrell et al. 2003, Saji and Yamagata 2003, Trenberth 1997, Ummenhofer et al. 2009, Ward et al. 2014) as well as crop productivity (Anderson et al. 2017, Ceglar et al. 2017, Heino et al. 2018, Iizumi et al. 2014, Yuan and Yamagata 2015) worldwide. The most notorious climate oscillation, the El Niño Southern Oscillation (ENSO), is the most significant driver of global climate variability (Trenberth 1997), while two other prominent and widely studied climate oscillations, the Indian Ocean Dipole (IOD) (Saji et al. 1999), and the North Atlantic Oscillation (NAO) (Hurrell 1995), are also known to affect temperature and precipitation patterns around the globe (Hurrell et al. 2003, Saji and Yamagata 2003).

All of these three climate oscillations have been shown to significantly impact crop productivity in global (Heino et al. 2018, Iizumi et al. 2014) as well as regional studies (Anderson et al. 2017, Ceglar et al. 2017, Yuan and Yamagata 2015).~~) studies.~~ The IOD, for example, strongly affects Australia's drought patterns (Ummenhofer et al. 2009) and crop production (e.g. wheat (Yuan and Yamagata 2015)), while NAO has been shown to impact crop productivity particularly in Europe (Ceglar et al. 2017), but also in the Middle East, Northern Africa and some parts of Asia (Heino et al. 2018, Wang and You 2004). However, the largest fingerprint of these three oscillations is that of ENSO, which has been found to impact crop productivity in all continents that produce crops (Anderson et al. 2019, Iizumi et al. 2014).

As the phase and development of ENSO, IOD and NAO can potentially be forecasted from several months (IOD, NAO (Luo et al. 2008, Scaife et al. 2014))~~ potentially~~ up to one year (ENSO (Luo et al., 2005, Ludescher et al. 2014)) in advance, considerable possibilities arise from understanding the impacts of these climate oscillations on crop production. If these impacts were better understood, it would allow national food agencies, international aid organizations, as well as food industries and farmers to prepare for varying crop development conditions. This would yield great benefits in increasing the resilience of the global food system to climate related shocks.

Until now, global scale studies about the relationship between crop production and climate oscillations have relied on individual satellite-based (Iizumi et al. 2014) or single-model simulated (Heino et al. 2018) crop yield estimates. The data produced and published in phase 1 of the global gridded crop model intercomparison (GGCMI) of the Agricultural Model Intercomparison and Improvement Project (AgMIP) now allows conducting assessments related to crop yield variability with an ensemble of models and a range of fertilizer use and irrigation set-ups (Elliott et al. 2015, Müller et al. 2019). Given the large variation in crop yield estimates across models (Müller et al. 2017, Rosenzweig et al. 2014), using an ensemble of models can allow for more robust estimates with better quantification of uncertainty in estimated yield impacts than using a single model.

By using the historical crop yield output derived from a multi-model ensemble of GGCMI, we aim to analyse the impacts of ENSO, NAO and IOD on maize, rice, soybean and wheat yields at the global scale. This extends previous studies, which are based on ~~individual~~ crop yield estimates from single datasets (Heino et al. 2018, Iizumi et al. 2014) and have assessed the impacts of solely ENSO (Iizumi et al. 2014) or the impacts of multiple oscillations on an aggregated crop productivity proxy (Heino et al. 2018). Further, since it is well known that agricultural management can have a major influence on climate induced crop yield variations (Challinor et al. 2014, Müller et al. 2018a~~2018~~), we assess these impacts in different irrigation and fertilizer use scenarios. As a result, we are able to highlight potential management options to mitigate the impacts of these oscillations on crop production. In the Results and Interpretation section we also compare our results with previous work in order to provide a comprehensive overview of known phenomena while avoiding repetition.

2 Data and methods

2.1 Physically simulated crop yield data

Global data of physically simulated maize, rice, soybean and wheat yield (t ha^{-1}) were obtained from~~for~~ the global gridded crop models'~~models~~ (GGCMs) simulations included in phase 1 of the GGCMI of AgMIP (Elliott et al. 2015, Müller et al. 2019).~~).~~ While most of the 12 models included here simulate the growth of all four target crops, a few simulate only some (Table 1): EPIC-TAMU (maize and wheat), pAPSIM (maize, soybean and wheat), and PEGASUS (maize, soybean and wheat). A recent study evaluated the performance of the models, included in the GGCMI of AgMIP, in reproducing reported historical yield anomalies, and did not find any GGCM clearly superior to any other (Müller et al. 2017, Figure S1), thus highlighting the benefits of utilizing a model ensemble in yield variability assessments to account for uncertainty in individual model results.

Table 1. Crop yield data used in this study. 'All' refers to all of the crops included in this study, i.e. maize (M), rice (R), soybean (S) and wheat (W). Three model configurations were utilized: harmonized growing season and nutrient input (fullharm), harmonized growing season and no nutrient limitation (harm-suffN), and standard model-specific assumptions (default). Details about the climate forcing data availability are given in the footnotes.

	Crops included for different model configurations				
	fullharm	**harm-suffN**	**default**	**Model Reference**	**Data reference**
CGMS-WOFOST	-	-	All[1]	(de Wit and Van Diepen 2008)	Hoek and de Wit (2018a, b, c, d)
EPIC-Boku	All[1,2]	All[1,2]	All[1,2]	(Izaurralde et al. 2006, Williams 1995)	Schmid (2018a, b, c, d)
EPIC-IIASA	All[1]	All[1]	All[1]	(Izaurralde et al. 2006, Williams 1995)	Balkovic et al. (2018a, b, c, d)
EPIC-TAMU	M, W[1,2]	M, W[1,2]	-	(Izaurralde et al. 2012)	Reddy et al. (2018a, b)
GEPIC	All[1]	All[1]	All[1]	(Folberth et al. 2012, Liu, J. et al. 2007, Williams 1995)	Folberth (2018a, b, c, d)
LPJ-GUESS	-	All[1,2]	All[1]	(Lindeskog et al. 2013, Smith et al. 2001)	Pugh et al. (2018a, b, c, d)
LPJmL	-	All[1,2]	All[1,2]	(Bondeau et al. 2007, Waha et al. 2012)	Müller (2018b~~2018a, b~~, c, d, e)
ORCHIDEE-crop	M[1,3], R[1,3], S[1,3], W[1]	M[1,3], R[1], S[3], W[1]	M[1], R[1,3], S[1], W[1]	(Wu et al. 2016)	Wang and Ciais (2018a, b, c, d)
pAPSIM	M, S, W[1,2]	M, S, W[1,2]	M, S, W[1,2]	(Elliott et al. 2014, Keating et al. 2003)	Elliott (2018a, b, c)
pDSSAT	All[1,2]	All[1,2]	All[1,2]	(Elliott et al. 2014, Jones et al. 2003)	Elliott (2018d, e, f, g)
PEGASUS	M, S, W[1,2]	M, S, W[1]	M, S, W[1]	(Deryng et al. 2011, Deryng et al. 2014)	Deryng (2018a, b, c)
PEPIC	All[1]	All[1]	All[1]	(Liu, W. et al. 2016, Williams 1995)	Liu and Yang (2018a, b, c, d)

1) AgMERRA, Timespan: 1980-2010

2) Princeton, Timespan: 1948-2008

3) Princeton, Timespan: 1979-2010

Yield variability in the GGCMs included in GGCMI is mainly driven by weather circumstances and CO_2 concentration, while soil conditions and agricultural management practices are considered static (Müller et al. 2019~~2017~~). To account for varying assumptions of growing season and fertilizer use, in GGCMI, model simulations were conducted for three configurations:

standard model assumptions (default), harmonized growing season and nutrient input (fullharm), and harmonized growing season with no nutrient limitation (harm-suffN). For the default configuration each modelling group used their own model assumptions. In the harmonized model set-ups, crop planting and harvesting dates were standardized among the models and are ~~are based on~~ literature-based (Elliott et al. 2015),~~,~~ while fertilizer application rates are either unlimited (harm-suffN) or based on published data (fullharm). Further, all of the GGCMI simulation results are provided separately for irrigated and rainfed conditions. In the irrigated simulation settings, no restrictions on water availability are considered (Müller et al. 2019). In GGCMI, the models simulate only a single growing season per year.~~2017).~~ Two models included in the GGCMI archive, PRYSBI2 and CLM-Crop, were excluded from this study because either the harmonization of growing season provided unreliable results (CLM-Crop) or the model does not distinguish between rainfed and irrigated crops (PRYSBI2).

The “actual” cropping scenario, used in the main analyses (with ~~(~~literature based shares of rainfed and irrigated areas, see Sect. 2.3),~~2.3) cropping scenario, used in the main analyses,~~ utilizes the fullharm set-up, and the harm-suffN setting for LPJ-GUESS and LPJmL, which do not consider nitrogen limitation and thus cannot harmonize on fertilizer settings (Table 2). For comparison, the sensitivity analysis (see Sect 2.4) for the actual cropping scenario was repeated with the default model set-up (see Supplement), while the harm-suffN scenario was used in assessing the impacts of the oscillations in fully fertilized conditions.

Table 2. The management scenarios used in this study. The actual set-up is used in the main analyses, while the fully irrigated, rainfed, fully fertilized, and the fully irrigated and fertilized management scenarios are used for comparing the impacts in different cropping systems.

Management scenario	Irrigated areas	Fertilizer use
Actual	Literature based	Literature based*
Fully irrigated	All areas irrigated	Literature based
Rainfed	No areas irrigated, all areas rainfed	Literature based
Fully fertilized	Literature based	Fully fertilized
Fully irrigated and fertilized	All areas irrigated	Fully fertilized

***)** For LPJ-GUESS and LPJmL, limitations on fertilizer use are not considered. These models are excluded from the “Actual” scenario for the comparison with varying fertilizer use.

This study utilizes simulations driven with two historical meteorological forcing data sets (bias-corrected re-analysis weather data sets): AgMERRA (Ruane et al. 2015) and Princeton Global Forcing data set (Sheffield et al. 2006) (Table 1). AgMERRA was selected as the main climate input for this study, as a large number of GGCMs supplied data for this climate forcing data set, while the Princeton data was selected for reference due to its long timespan and previous use in a similar study (Heino et al. 2018). A detailed description of the GGCMI phase 1 modelling protocol can be found in Elliott et al. (2015) and the output data set is described by Müller et al. (2019)).

2.2 Climate oscillation data

To represent the historical fluctuations of ENSO, IOD and NAO, the following indices were chosen: the Japan Meteorological Agency (JMA) SST Index (Florida State University 2015), the SST Dipole Mode Index (NOAA ~~Japan Agency for Marine-~~Earth System Research Laboratory 2017~~Science and Technology 2010~~, Saji et al. 1999), and Hurrell's North Atlantic Oscillation Index (primary component (PC)-based) (Hurrell 1995, National Center for Atmospheric Research 2015), respectively. These indices were selected because they are all well established and have already been used in several studies related to crop production (Heino et al. 2018, Kim and McCarl 2005, Yuan and Yamagata 2015). For ENSO, the Niño 3.4 index (NOAA Earth System Research Laboratory 2019) was also tested given its common use in ENSO related studies (Stuecker et al. 2017, Zhang et al. 2015), with results shown in the Supplement. The indices~~They~~ were transformed to annual values by calculating the mean index for the months when the oscillations tend to have the strongest signal, according to existing sources, (i.e. December, January, February for ENSO (Trenberth 1997) and NAO (Hurrell et al. 2003); September, October and November for IOD (Saji et al. 1999).~~)).~~ This therefore only tests for relationships with a phase-locked measurement of the oscillation rather than investigating intra-annual temporal effects. Using seasonal or monthly data increases the number of significance tests for a given location and therefore the risk of false positives, and interpretation of results would require understanding of how climate oscillations, local weather conditions and yield are connected over time. However, it requires accurate, high-resolution global crop calendars which are not available. Finally, in order to make the oscillation indices comparable with each other, each oscillation index time series was standardized (by subtracting the ~~annual index values by their~~ average index value from the annual values and dividing by~~with~~ their standard deviation).

2.3 Crop yield data aggregation and de-trending

The gridded crop yields were allocated to ~~oscillation specific~~ annual yields based on the sowing~~harvesting~~ dates used in the harmonized GGCMI simulations. The~~Hence, oscillation specific~~ "harvest year t" is assigned to all harvests from growing seasons that ~~years", which~~ start between May of ~~from~~ the actual year (t) and April of ~~first day that~~ the next year (t+1). This definition~~respective oscillation index is calculated, are defined. For NAO and ENSO (oscillation index calculated~~ for harvest years was selected, because it ensures that~~DJF),~~ the average lifespans of all these oscillations are within~~harvest year is from December 1st to November 30th, while for IOD (calculated for SON)~~ the harvest year, and thus many of the major known teleconnections of these oscillations during the crop growing season are included in the analysis (e.g. in Australia, Africa, and South America). ~~is from 1st of September until end of August.~~

The crop yield data were aggregated spatially to the geographical scale of Food Production~~Producing~~ Units (FPUs), which divide the world into 573 spatial units that are hybrids of river basins and administrative (economic) areas (Kummu et al.

2010). For the actual cropping scenario, rainfed and irrigated crop yields were combined by calculating the mean yield as the total production divided by the total harvested area across both cropping systems, using literature based values about harvested area (Portmann et al. 2010). The aggregation for irrigated and rainfed scenarios was conducted similarly by dividing total production by harvested areas but assuming that all cropland is either irrigated or rainfed, respectively.

In order to extract the interannual variability of the crop yield data, they were de-trended. This was conducted by subtracting a five-year moving average yield from the annual yield values (three-year average at both ends of the time series),~~) yield from the annual yield values,~~ similarly to several previously conducted studies about yield variability (Iizumi et al. 2014, Iizumi and Ramankutty 2016, Müller et al. 2017, Müller et al. 2018a~~2018~~). The anomalies were then divided by five-year (or three-year) averages to obtain proportional annual deviation from the normal values. The equation of the procedure is shown below:

$$\Delta Y_{f,s,m,c,t} = \frac{Y_{f,s,m,c,t} - \bar{Y}_{f,s,m,c,t}}{\bar{Y}_{f,s,m,c,t}} * 100, (1)$$

where $\Delta Y_{f,s,m,c,t}$ denotes relative yield anomaly for each FPU (f), scenario (s), model (m), crop (c) and year (t) compared to the average yield ($\bar{Y}_{f,s,m,c,t}$) for the moving~~rolling~~ time window around year t.~~in question.~~ The use of a shorter time window at the beginning and end of the yield time series allows longer de-trended time series, and it is assumed that it would rarely lead to errors about the sign of yield anomalies and thus the derived relationships between climate oscillation and yield anomalies. Other studies have tested other de-trending methods as well, but have found no major impact from the method selected (Iizumi et al. 2014, Iizumi and Ramankutty 2016, Müller et al. 2017).

2.4 Crop yield sensitivity to the oscillations

The sensitivity of actual crop yield to the oscillations was investigated using a multivariate linear regularized ridge regression model, with the oscillation indices as explanatory variables~~variable~~ and the annual crop yield anomalies as dependent variable. The ridge regression framework was selected because it allows accounting for correlations among the explanatory variables (here oscillation indices). ~~In this linear regression model, the slope represents sensitivity.~~ For the main analysis (actual scenario), the regression~~, a linear fit~~ was calculated for each FPU separately using crop yield anomaly time series from all GGCMs that simulate the crop in question with the AgMERRA climate input (N=216-297, depending on crop). Hence, we utilize the crop yield time series of all the models in fitting the regression. In the regression model, the slope coefficients represent sensitivity. The optimal regularization value, for the regression, was selected by performing a generalized cross-validation (tested regularisation values ranged between 10^{-6} and 10).

$$\cancel{[S_{f,s,c,o}\ i_{f,s,c,o}] = (I_{o,t}{}^{T} I_{o,t})^{-1} I_{o,t}{}^{T} \Delta Y_{f,s,m,c,t}, (2)}$$

where $S_{f,s,c,o}$ and $i_{f,s,c,o}$ are the slope (i.e. sensitivity) and intercept of the regression model for each FPU (f), scenario (s), crop (c), and oscillation (o), respectively, and $I_{o,t}$ is the oscillation index. The existence of significant relationships~~a linear relationship~~ was assessed by calculating a multivariate ridge regression ~~Pearson's correlation~~ from ~~a~~ random bootstrap samples~~sample~~ (N = 1,000, with replacement) of crop yield–oscillation index combinations. Statistical significance therefore tests the robustness of observed ridge regression coefficients across different samples drawn from the time series. The optimal regularization value was selected for each bootstrap sample as described above, which follows the principle described in Abram et al. (2016).~~variable pairs.~~ The linear relationship was defined to be significant ($p < 0.1$), if 95 % (two-sided test) of the sampled sensitivity values~~correlations~~ were either larger or smaller than zero. Thus, a 10 % probability was accepted of wrongly classifying a linear relationship as significant. Note that the relatively high risk level in statistical regression ($p < 0.1$) is commonly used in global climate-yield analysis because of the limited access to high quality yield data at the global scale (e.g., Ray et al., 2015). To check robustness of results, the same analysis was also conducted utilizing the crop yield data derived using~~with~~ the Princeton climate input, different model configurations as well as individual models and average weather (soil moisture and temperature) conditions (Martens et al. 2017, Ruane et al. 2015) during the growing season.~~.~~ Further, to illustrate the effect of using phase-locked indices rather than investigating intra-annual temporal variation (see Section 2.2), the sensitivity of crop yield to these oscillations was also assessed by using the average harvest season oscillation indices as explanatory variable (see Supplement).

2.5 Average crop yield anomalies during strong oscillation phases

The crop-specific average yield anomalies observed during strong oscillation phases were investigated for the actual cropping scenario. The crop yield changes that occur during years when the oscillations are in their strong phases were summarized by the median crop yield anomaly (in percent~~percentage~~) of those years. The median anomaly was calculated using all the GGCMs that simulate the crop in question (N=216-297, depending on crop) for the actual scenario with AgMERRA climate input. Strongly negative (positive) phases of the oscillations were defined as the years when the respective oscillation index was smaller (larger) than the 25th (75th) percentile of all yearly index values ($N_{anomaly}$ = 54-74, depending on crop).~~.~~ The statistical significance ($p < 0.1$) of the changes was assessed by bootstrapping (n = 1,000, with replacement) the crop yield anomalies, and calculating the median of each bootstrap sample. If over 95 % (two-tailed test) of the sample of medians~~means~~ were either larger or smaller than zero, the change was considered statistically significant. Statistical significance therefore tests the robustness of observed anomalies across different samples drawn from the time series.

2.6 Impacts in different cropping systems

To assess how expanding or reducing the extent of irrigated area, and increasing fertilizer use would change the impacts of climate oscillations on crop yields, compared to the actual scenario, the main sensitivity analysis (see description above – Sect. 2.4) was conducted for a set of scenarios (Table 2): i) all cropland was only rainfed (with fullharm setup), ii) all cropland was fully irrigated (fullharm), iii) all cropland was fully fertilized (actual irrigation with fullharm-suffN), and iv) all cropland was fully irrigated and fertilized (fully irrigated with harm-suffN). In addition to analysing how the above mentioned four scenarios compare against the actual scenario, the fully irrigated and rainfed scenarios were also compared. To quantify how the impacts in these cropping systems vary, average sensitivity magnitudes were compared for each crop. Specifically, for a pair of scenarios, the average difference of their absolute sensitivity values was calculated across all oscillations and FPUs, where at least one of the scenarios shows a significant sensitivity. To obtain a measure relative to the actual (or irrigated when comparing irrigated and rainfed scenarios) scenario, the average difference values were divided with the average sensitivity magnitude of the actual (or irrigated) scenario for the FPUs included. The corresponding equation is:

$$\Delta S_{s12,c} = \sum_{o,f} \frac{|S_{s1,c,f,o}| - |S_{s2,c,f,o}|}{\overline{|S_{s1,c,f,o}|}} \Big/ n_{F,O} * 100\ \%, \ (2) \quad \cancel{\Delta S_{s12,c} = \sum_{o,f} \frac{|S_{s1,c,f,o}| - |S_{s2,c,f,o}|}{\overline{|S_{s1,c,f,o}|}} \Big/ n_{F,O} * 100\ \%, \ (3)}$$

where at least of one $|S_{f,s1,c,o}|$ or $|S_{f,s2,c,o}|$ is statistically significant. f, $s \in \{s1, s2\}$, c, and o are indices of FPU, management scenario, crop, and oscillation respectively. $\Delta S_{s12,c}$ denotes the average proportional sensitivity difference of each crop (c) between the scenarios, while $S_{f,s1,c,o}$ and $S_{f,s2,c,o}$ represent the sensitivity in the respective management scenarios $s1$ and $s2$. $n_{F,O}$ is the number of cases (oscillation and FPU) where at least one of the scenarios has a significant sensitivity.

For each crop, to assess whether the mean sensitivity magnitude difference is statistically significantly different from zero, a distribution of the mean sensitivity magnitude difference was created by calculating the average from bootstrapped (N = 1,000, with replacement) difference values of each FPU and oscillation. For the comparisons with varying fertilizer use, only those nine GGCMs which have data for both ‘fullharm’ and ‘harm-suffN’ settings and thus simulate nutrient stress (Table 1), were included.

3 Results and Interpretation

3.1 Global extent of climate oscillation impacts

Globally, climate oscillations have widespread effects on crop yields (Table 3~~2~~), but both the direction and magnitude of impacts vary spatially and across crops (Fig. 1). Out of the oscillations studied here, ENSO shows the widest impacts on yields of maize~~rice~~ (statistically significant sensitivity in 51~~55~~ % of harvested areas), wheat (49 %) and rice (48~~soybean (66~~ %), while IOD and ENSO both show a similar extent of impacts on the yields of soy (53 %~~wheat~~ and ~~maize (45~~ 50 %, respectively) (Table 3). Generally,~~%).~~ NAO seems to have the smallest impacts on the yields of the crop types inspected here in terms of harvested areas, although it still shows relatively strong influence on wheat (42~~37~~ %) and maize (35~~27~~ %) yields. In terms of sensitivity direction, it is notably more widespread for yield to increase~~decrease~~ towards the positive phase of ENSO (i.e. El Niño) for all crop types inspected here~~maize, rice and soybean~~ (i.e. positive~~negative~~ sensitivity). For IOD and NAO, the results are more mixed, though both show larger harvested areas where yield decreases~~increases~~ towards the positive phase for maize~~wheat~~. These results align with~~are backed up by~~ crop yield anomalies during strong oscillation phases, as they also show widespread average impacts (Table S2~~crop yield anomalies during strong oscillation phases (Table S1~~).

Table 3~~2~~. Extent of significant sensitivity. Crop-specific harvested area (10^6 ha) extent (and percent of total crop-specific harvested area), where actual crop yield shows statistically significant positive (+) or negative (-) sensitivity to ENSO, IOD and NAO, i.e. there is a statistically significant (two-sided p-value < 0.1) linear relationship between crop yield anomalies and the studied oscillations (see Methods). Extent affected by significant anomalies is shown in Table S2~~S1~~.

	ENSO		IOD		NAO	
Sensitivity	−	+	−	+	−	+
Maize	30 (20~~48 (32~~ %)	46 (31~~25 (17~~ %)	36 (24~~32 (21~~ %)	18 (12~~44 (29~~ %)	44 (29~~30 (20~~ %)	10 (6~~11 (7~~ %)
Rice	31 (19~~68 (41~~ %)	47 (29~~23 (14~~ %)	22 (13~~64 (38~~ %)	16 (10~~19 (11~~ %)	1 (0~~6 (4~~ %)	8 (5~~18 (11~~ %)
Soybean	6 (8~~39 (52~~ %)	31 (42~~10 (14~~ %)	32 (42~~23 (31~~ %)	8 (11~~21 (28~~ %)	22 (29~~9 (12~~ %)	6 (8 %)
Wheat	28 (13~~45 (21~~ %)	77 (36~~54 (25~~ %)	45 (21~~33 (16~~ %)	46 (21~~76 (35~~ %)	20 (10~~24 (11~~ %)	69 (32~~55 (26~~ %)

3.2 Impacts in different areas

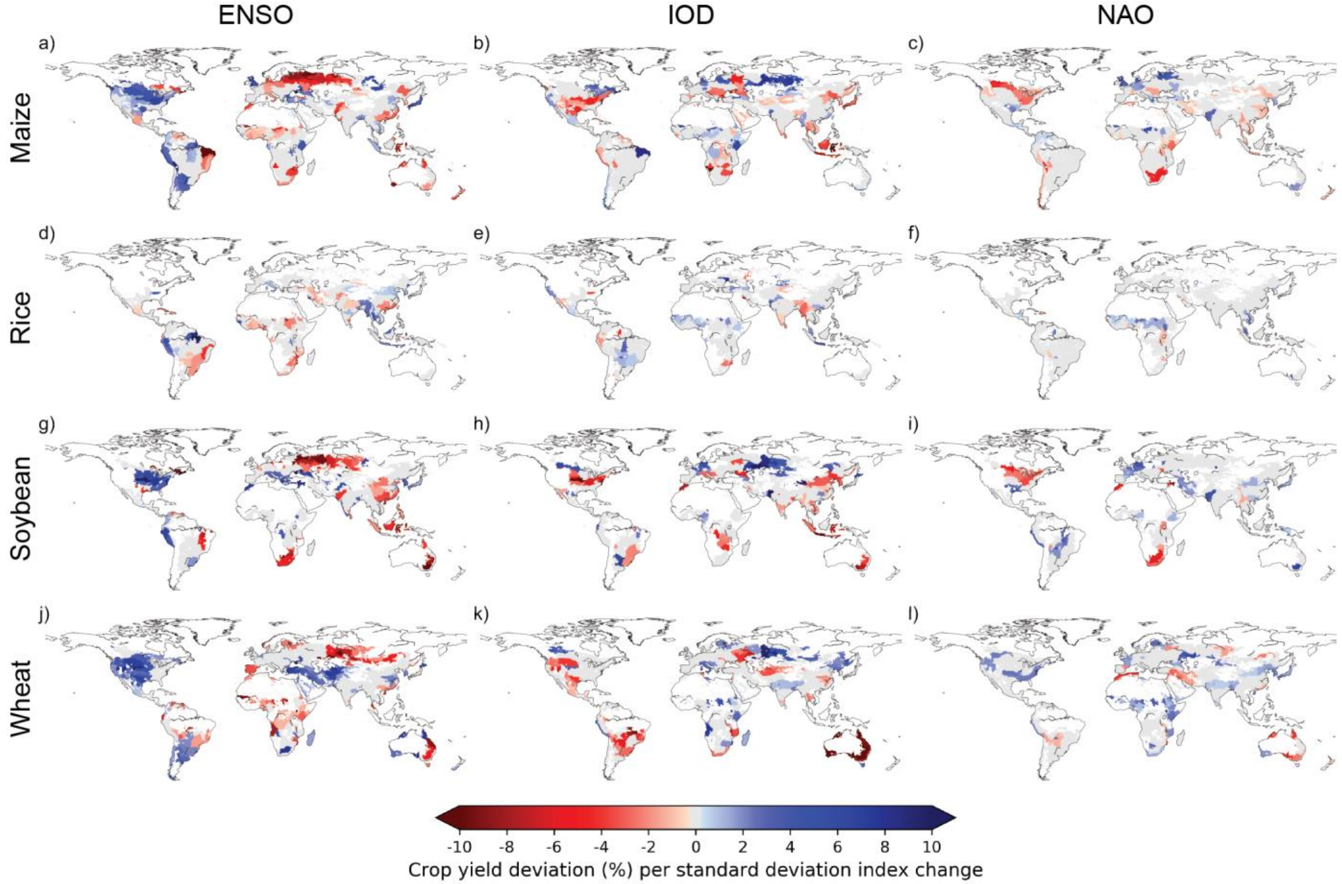
ENSO's relationship with crop yield seems to provide the most distinct spatial patterns across the crop types, crop models and oscillations studied here (Figs 1-3, Figs S4-S10~~S1-S6~~, Supplementary zip-file). Crop yields tend to decrease towards the positive phase of ENSO (El Niño) in a large proportion of sub-Saharan~~southern~~ Africa, as well as eastern parts of South America and Australia~~,~~ while yields seem to increase towards the positive phase on the coast of Peru and North America~~eastern Africa~~ (Fig. 1, global regions mapped in Fig. S1). In general, these results align well with the spatial patterns found in existing studies on the Palmer Drought Severity Index (Dai et al. 1998) as well as soil moisture and temperature anomalies (Figs S2-S3).~~crop productivity (Heino et al. 2018).~~ Also, in terms of model and methodological agreement, consistent increase (decrease) of wheat yields in ~~eastern South Asia and~~ parts of the Middle East can be observed for ENSO towards its positive (negative) phase (Figs 1-3, Figs S11-S12). For the southern tip~~parts~~ of Africa~~North America~~, wheat and soybean seem to be related with opposite impacts. This is potentially because of differences in harvest timing and the related weather conditions; ~~winter~~ wheat is harvested in~~before~~ the autumn~~summer~~, while soybean is harvested the following spring, and thus~~autumn, which~~ is more exposed~~when an ENSO event of opposite sign might have started~~ to the drier conditions related to ~~develop (Anderson et al. 2017). If the sensitivity for soybean is calculated for~~ ENSO during the boreal winter (Fig. S2, Philippon et al. 2012) .~~autumn, it is closer to what is observed for wheat (Fig. 1, Figs S7-S8).~~

When comparing our results to a study about ENSO's crop yield impacts, which utilized satellite-based crop yields (Iizumi et al. 2014, Iizumi et al. 2018a), the agreement of the impacts varies. Our results agree with existing studies for example for large parts of Africa and eastern Asia, where El Niño is mostly related to negative impacts, while results do not agree ~~as well~~ in

North America (wheat, maize) and Australia~~central South America~~ (maize~~, soybean~~). However, it should be noted, that these differences are no surprise, since it has been shown that only a third of global crop yield variability can be attributed to seasonal climate variation (Ray et al. 2015). In contrast to the satellite-based data, the models used here deliberately focus on weather impacts on crop yield, and do not consider the impacts of e.g. multiple cropping or weather triggered pest outbreaks and management responses, which can also be major contributors to crop yield variations.

For IOD, strong and consistent impacts (Figs 1-2) among crop models (Fig. 3) can be observed in eastern Australia, especially for soybean and wheat (Figs 1-3), where the IOD is related to drier and warmer weather conditions (Figs S2-S3).~~).~~ This corroborates a previous study conducted on the relationship between IOD and wheat yields, which showed that around 40 % of Australia's wheat yield variability can be attributed to the IOD (Yuan and Yamagata 2015), and where the oscillations are together also able to explain a substantial portion of crop yield variability (>25 %, Fig. S13).~~).~~ Further, consistent results among models and methods (Figs 1-3) for IOD can be observed in parts of Eastern Europe~~Russia~~ and Central Asia, where the positive (negative) phase of the IOD is related to an ~~a decrease (~~increase (decrease) in wheat, maize and soybean yields. In~~ India,~~ Southeast Asia, and southern Africa, the impacts of the IOD vary between crops. For example, in Southeast Asia, rice~~southern Africa, wheat~~ shows a positive sensitivity (increasing yield towards the positive phase) while maize and soybean~~rice~~ show a negative one.~~, again, potentially because of different times of harvest and the related weather conditions.~~ In eastern China, maize, wheat~~rice~~ and soybean yield variability seems to be related to the IOD to some extent. However, these relationships are less certain, as they are not consistently found by the majority of the individual models (Fig.~~Figure~~ 3).

For NAO, the relationships are generally less certain in terms of model agreement compared to ENSO and IOD (Fig. 3). NAO's most significant impacts can be observed in eastern Europe and the Middle East on maize, soybean and wheat yields (Figs 1-2). In the Middle East, for the sensitivity of wheat and maize (soybean) ~~crop~~ yield to NAO seems~~tends~~ to be negative (positive~~increasing yield towards the negative phase~~), while mostly positive sensitivity is found in Europe and western Russia for maize, soybean and wheat.~~.~~ These results align with results from previous studies about weather patterns and crop productivity (Cullen et al. 2002, Heino et al. 2018, Hurrell et al. 2003). Although, the results for NAO are relatively similar between different model configurations (Figs S4-S6~~S2-S3~~), the results are not as consistent among the GGCMs as for the other oscillations (Fig. 3).



ENSO
IOD
NAO
a)
b)
c)
Maize
d)
e)
f)
Rice
g)
h)
i)
Soybean
j)
k)
l)
Wheat
-10 -8 -6 -4 -2 0 2 4 6 8 10
Crop yield deviation (%) per standard deviation index change

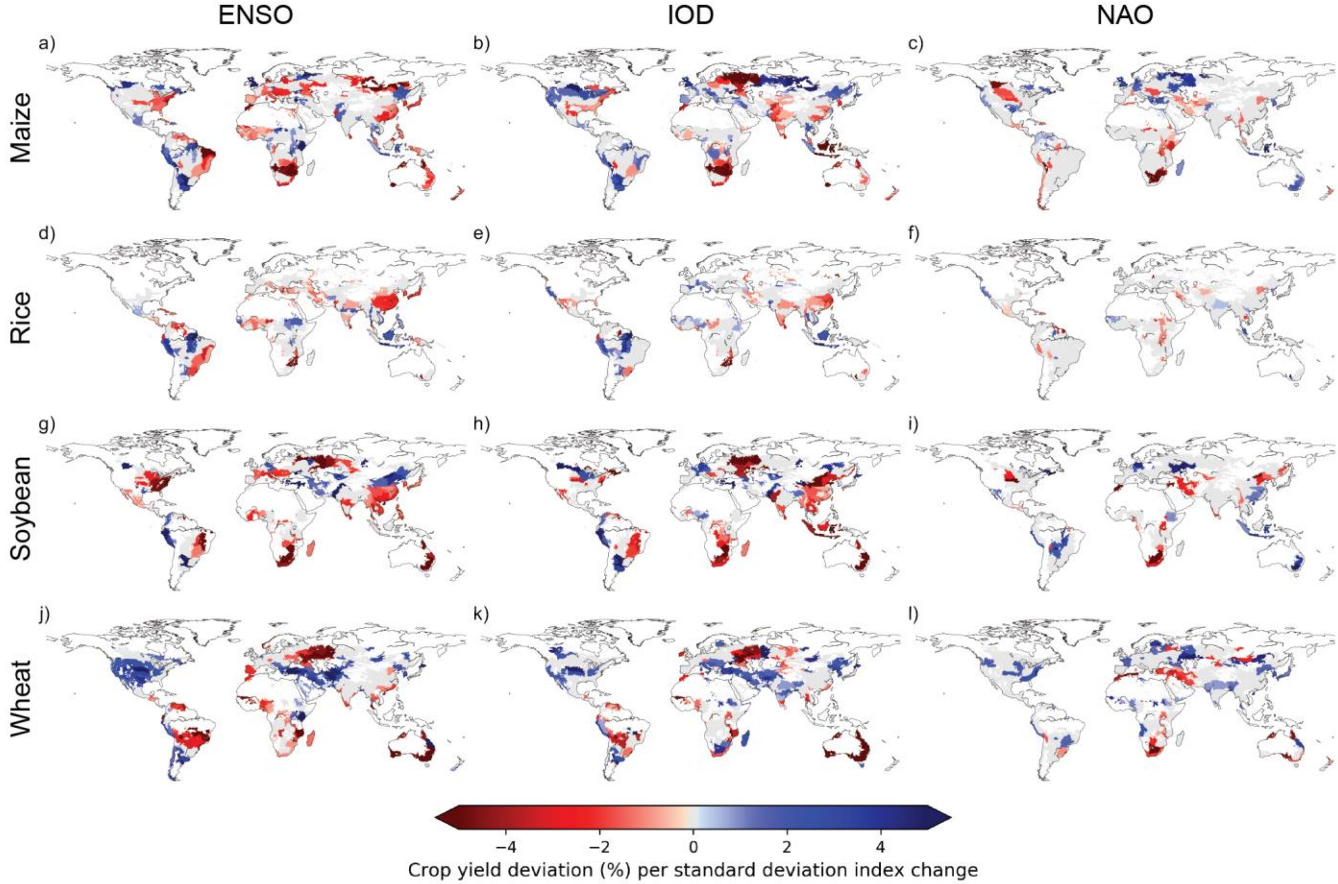
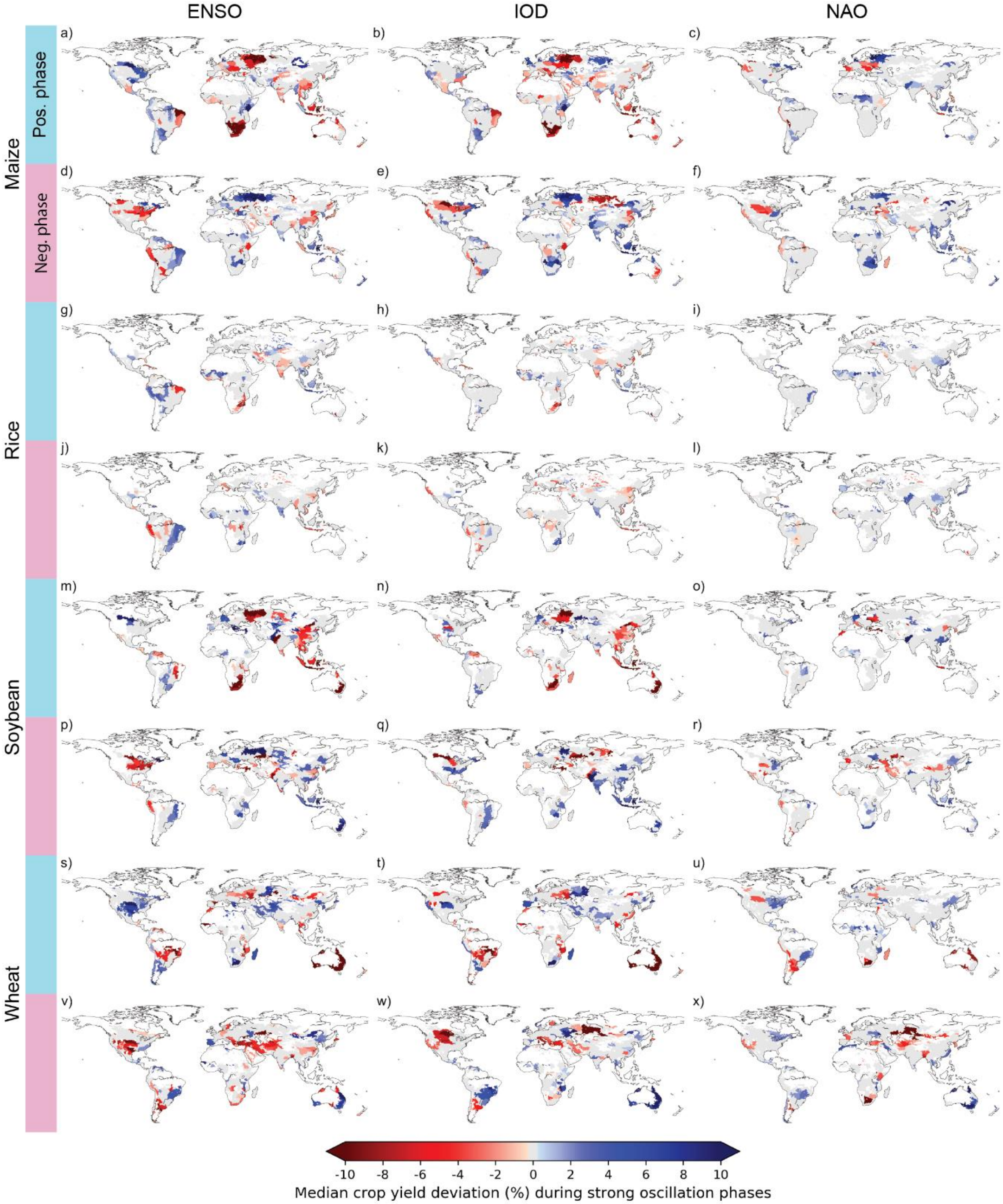


Figure 1. Actual maize (a-c), rice (d-f), soybean (g-i), and wheat (j-l) yield sensitivity to ENSO, IOD and NAO at FPU scale. The sensitivity values are derived using crop yield data from all GGCMs that simulate the crop in question with the AgMERRA climate input. Statistically insignificant (p > 0.1) sensitivity values are marked as zero (colour grey). White colour denotes that the crop in question is not produced in that area. Results with Princeton climate input and default model setup are shown in Figs S1 and S2, respectively. Median, maximum and minimum sensitivities as well as consistency across individual models are shown in Figs S3-S6, respectively. Results for individual models are shown in a Supplementary zip-file. Results with oscillation indices calculated in the harvest season are shown in Fig. S7, with the associated seasons shown in Fig. S8.


ENSO
IOD
NAO
Maize
Pos. phase
Neg. phase
Rice
Soybean
Wheat
a)
b)
c)
d)
e)
f)
g)
h)
i)
j)
k)
l)
m)
n)
o)
p)
q)
r)
s)
t)
u)
v)
w)
x)
-10
-8
-6
-4
-2
0
2
4
6
8
10
Median crop yield deviation (%) during strong oscillation phases

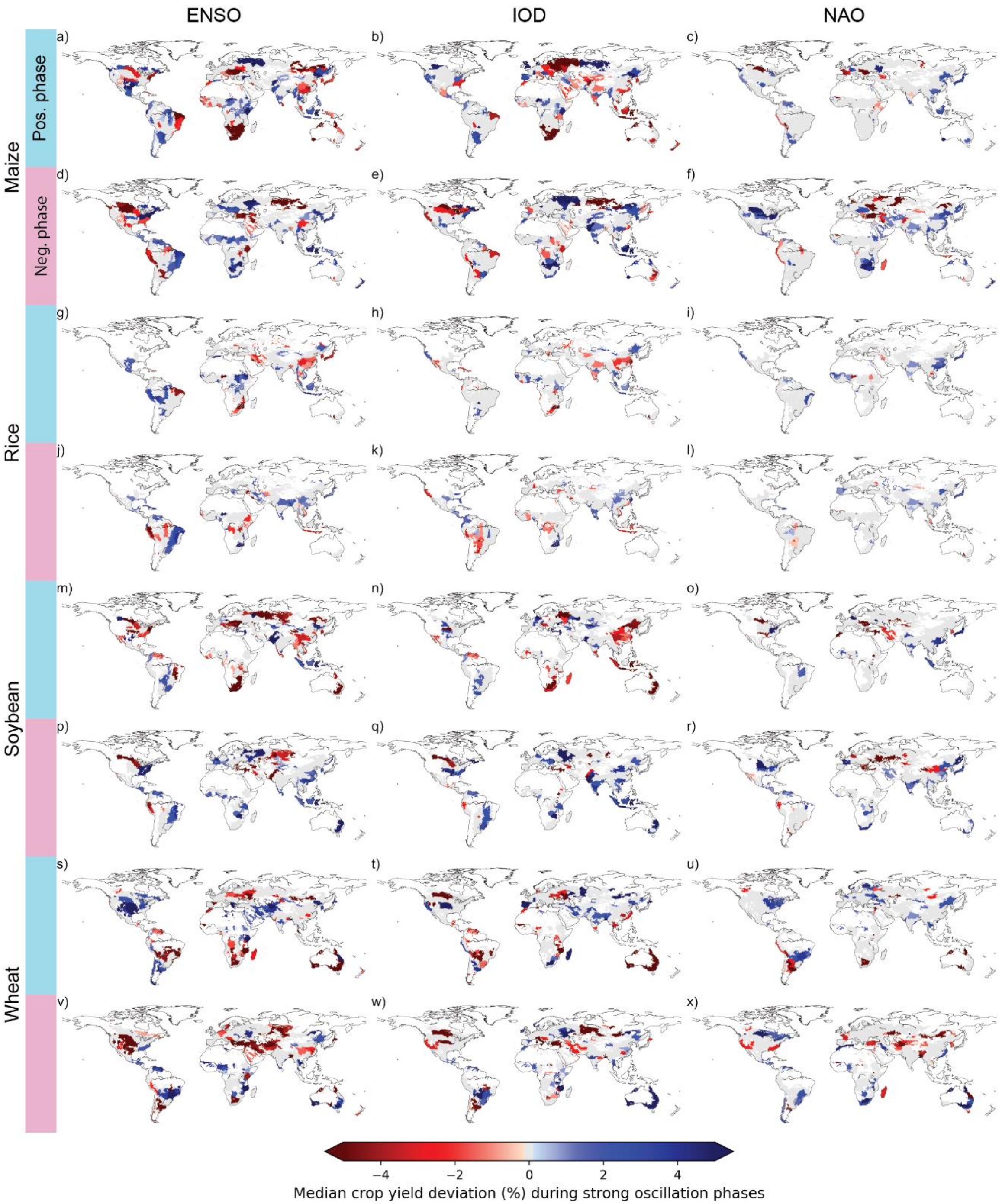
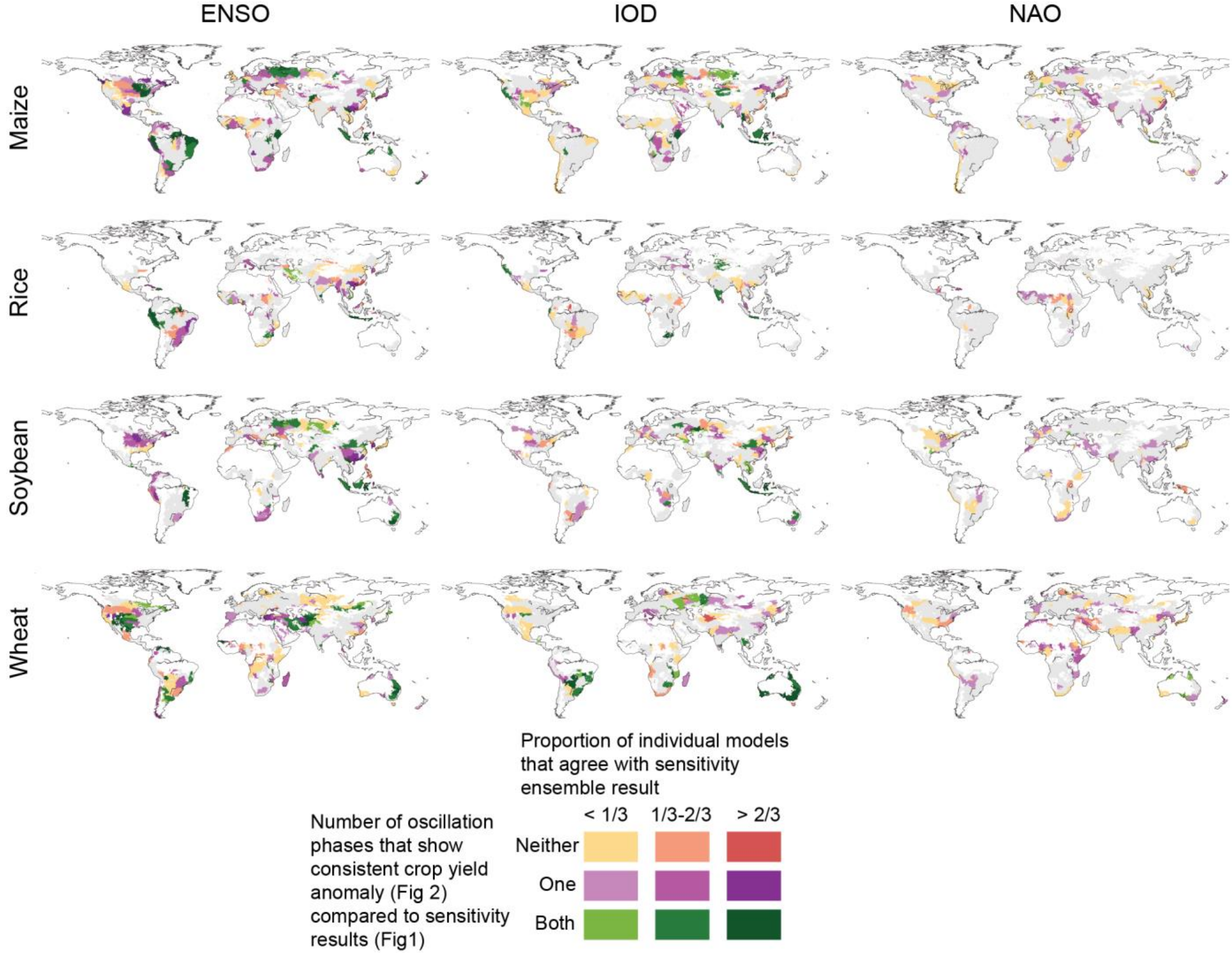


Figure 2. Actual maize (a-f), rice (g-l), soybean (m-r), and wheat (s-x) yield anomalies during strong phases of ENSO, IOD and NAO at FPU scale. The anomaly values are derived from a sample including crop yield data from all GGCMs that simulate the crop in question with the AgMERRA climate input. Statistically insignificant ($p > 0.1$) anomaly values are marked as zero (colour grey). White colour denotes that the crop in question is not produced in that area. Patterns are discussed in Sections 3.1 and 3.2.



ENSO
IOD
NAO
Maize
Rice
Soybean
Wheat
Proportion of individual models that agree with sensitivity ensemble result
< 1/3
1/3-2/3
> 2/3
Number of oscillation phases that show consistent crop yield anomaly (Fig 2) compared to sensitivity results (Fig1)
Neither
One
Both

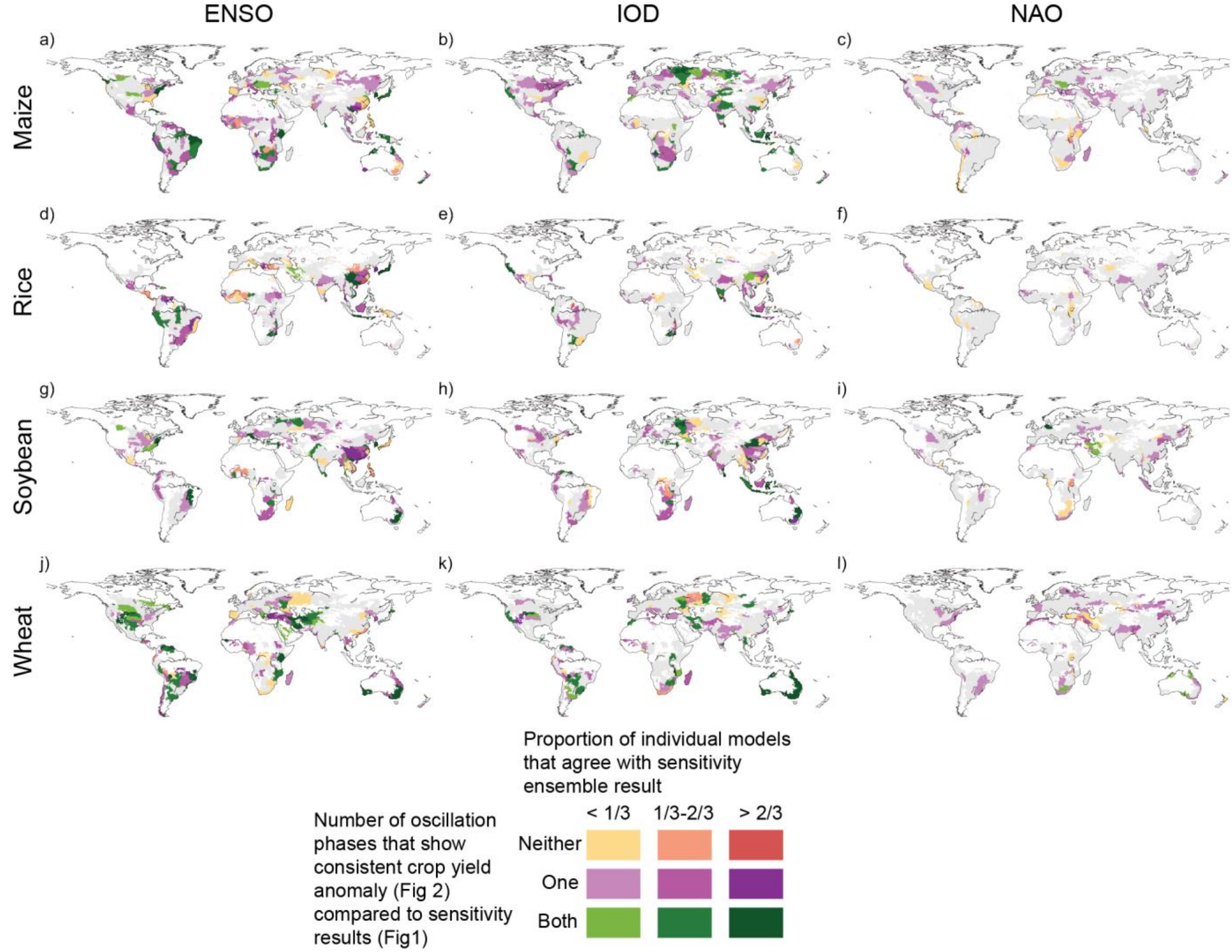


Figure 3. Summary of relationship between ENSO, IOD, and NAO and crop yields across~~Agreement between~~ models and methods for maize (a-c), rice (d-f), soybean (g-i), and wheat (j-l). The y-axis of the colour bar shows whether there is agreement between the sensitivity analysis (Fig. 1) and the average anomalies during strong oscillation phases (Fig. 2): '*Neither*' denotes that the strong oscillation phases are not related to significant average crop yield anomalies that are consistent with the sensitivity analysis, '*One*' means that either positive or negative oscillation phase shows a significant average anomaly that is consistent with the sensitivity result (e.g. positive sensitivity, and positive anomaly during a positive oscillation phase), '*Both*' means that both phases of the oscillations show consistent average anomalies during the strong oscillation phases (e.g. positive anomaly during a positive oscillation phase, and negative anomaly during a negative oscillation phase in an FPU with positive sensitivity). The x-axis of the colour bar shows the proportion of individual models that show significant sensitivity of same sign compared to the result from the ensemble analysis (see Fig. 1 above, Fig. S6 and Supplementary zip-files). Areas where the ensemble results do not show a statistically significant relationship are marked in grey, while white colour denotes that the crop in question is not grown in that area

3.3 Magnitude of impacts in different cropping systems

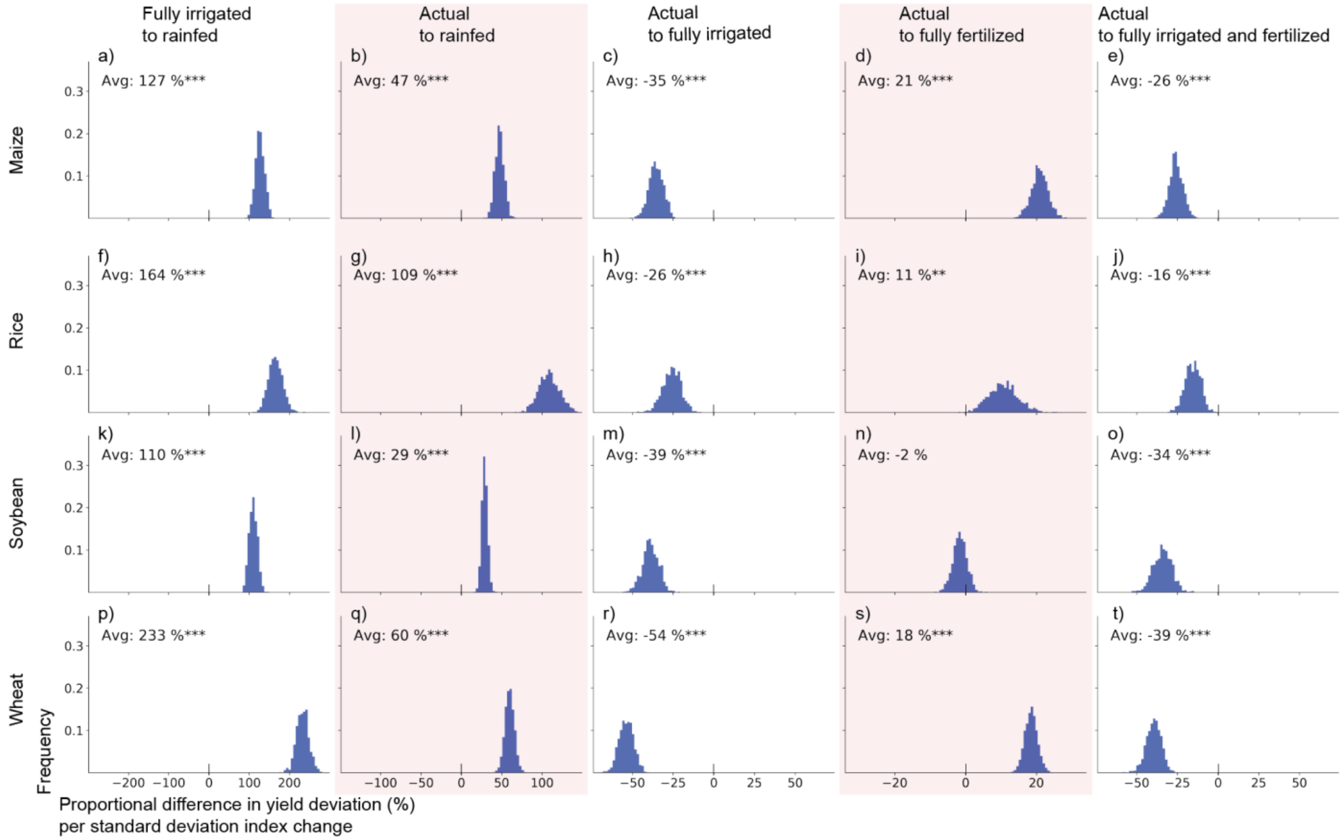
Irrigation plays a key role in reducing crop yield sensitivity to climate oscillations, with yield varying up to three times more (for wheat) across the range of oscillations when comparing fully irrigated and rainfed scenarios (Fig. 4). Comparing rainfed to actual conditions shows that irrigation has already substantially reduced the effects of climate oscillations on crop yields. The average difference in sensitivity is largest for rice, where average sensitivity would be over two times higher, i.e. yield would vary two times more across the range of the oscillations if all cropland was rainfed (Fig. 4g).~~.~~ The difference in sensitivity is smallest for soybean (29 %, Fig. 4l),~~30 %),~~ while maize and wheat show a relative increase in sensitivity ~~increase~~ of 47 % (Fig. 4b)~~68 %~~ and 60 % (Fig. 4q),~~63 %,~~ respectively. This ranking is expected, as the majority of rice harvested~~production~~ areas are~~is~~ irrigated (62 % globally)~~%)~~ and soybean has the smallest irrigated area share of these four crops (8 %), while maize (21 %) and wheat (31 %) fall in between (~~% globally,~~ Portmann et al. 2010).

Conversely, average sensitivity would be reduced~~smaller~~ if crops were fully irrigated without any limitations on water availability, compared to the actual situation, for all the inspected crop types. Benefits of further irrigation are limited by its current use, which might be why rice shows the smallest difference in average impacts (most of the rice harvested area is already irrigated, Fig. 4h). The average decrease in crop yield sensitivity to the oscillations is largest for wheat (54~~soybean (43~~ %, i.e. yield varying 54~~43~~ % less across the oscillations compared to actual conditions, Fig. 4r~~4~~) and soybean (39 %, Fig. 4m),~~wheat (48 %),~~ while maize shows a 35 % (Fig. 4c)~~34 %~~ average decrease.

Unlimited fertilizer (fully fertilized scenario) use yields statistically significantly larger average sensitivity compared to actual conditions for maize (21 %, Fig. 4d), rice (11 %, Fig. 4i)~~22 %)~~ and wheat (18 %, ~~%) (~~Fig. 4s~~3~~). For these crops, these climate oscillations have a stronger impact on yields in cropping systems that do not have limitations related to nutrient availability. This reflects previous research that has found increased crop yield variability under additional fertilizer inputs (Müller et al. 2018a~~2018~~). This is potentially because in low crop yield years, fertilizer use is not the main limiting factor, so yields are not significantly improved, while in years when climate conditions are suitable for crop growth, yields become even higher, which would increase the sensitivity value as well (Fig. S24). Note that this does not mean fertiliser fails to improve crop yields – only that it does not lead to more stable yields in the face of weather variability.~~S19).~~ Soybean has very little change in sensitivity under full fertilisation (Fig. 4n).~~.~~ This is likely because it is a legume and has lower nitrogen requirements – nitrogen availability is not even considered in soybean simulations in some models.

Combining both unlimited irrigation and fertilizers, all of the crop types show smaller average sensitivity compared to the actual cropping system scenario (Fig. 4). The decreased sensitivity due to increased irrigation dominates the increased sensitivity due to increased fertilizer use. However, the differences in sensitivity magnitude are large between crops, with wheat~~soybean~~ having the largest decreases in average sensitivity magnitude (39 %, Fig. 4t),~~41 %),~~ and rice having the smallest (16 %, Fig. 4j).~~12 %).~~

The above mentioned results can be observed spatially Supplementary Figs S14-S23~~S9-S17~~), which e.g. clearly show that, in most areas, the sensitivity magnitude is larger in the rainfed as well as fully fertilized scenarios, i.e. yields vary more across the range of the oscillation index. The spatial results also highlight areas with potential to reduce impact of oscillations, for example for ENSO in northern South America (soybean and rice) as well as for IOD in Australia (wheat), where high sensitivity to the respective oscillations can be observed for the actual scenario.


Fully irrigated
to rainfed
Actual
to rainfed
Actual
to fully irrigated
Actual
to fully fertilized
Actual
to fully irrigated and fertilized
Maize
Rice
Soybean
Wheat
a) Avg: 127 %***
b) Avg: 47 %***
c) Avg: -35 %***
d) Avg: 21 %***
e) Avg: -26 %***
f) Avg: 164 %***
g) Avg: 109 %***
h) Avg: -26 %***
i) Avg: 11 %**
j) Avg: -16 %***
k) Avg: 110 %***
l) Avg: 29 %***
m) Avg: -39 %***
n) Avg: -2 %
o) Avg: -34 %***
p) Avg: 233 %***
q) Avg: 60 %***
r) Avg: -54 %***
s) Avg: 18 %***
t) Avg: -39 %***
Frequency
Proportional difference in yield deviation (%)
per standard deviation index change

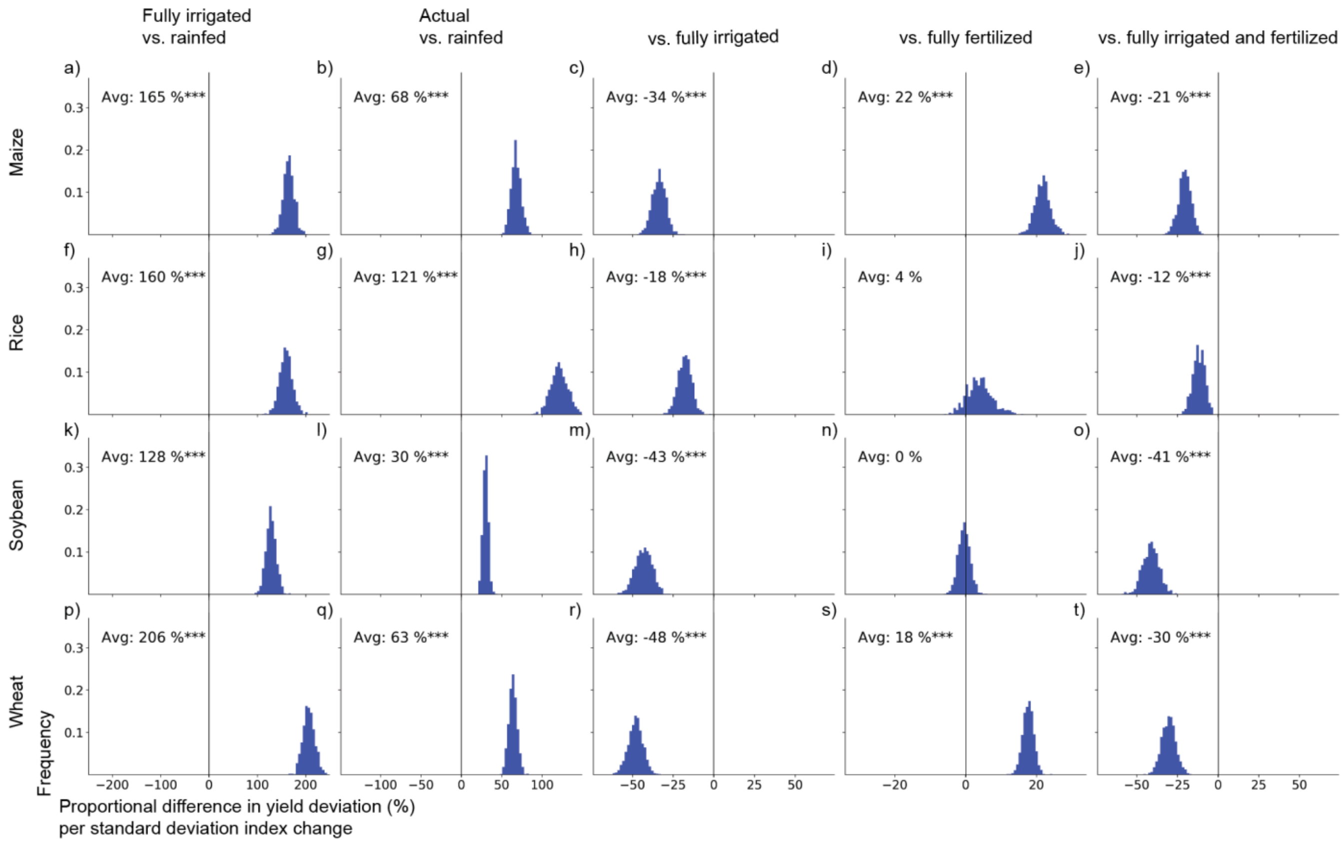


Figure 4. Relative average difference in sensitivity magnitude of maize (a-e), rice (f-j), soybean (k-o) and wheat (p-t) between a range of cropping scenarios through all the studied oscillations and FPUs. To quantify how the impacts in these cropping systems vary, average sensitivity magnitudes were compared for each crop. Specifically, for a pair of scenarios, the average difference of their absolute sensitivity values were calculated across all oscillations and FPUs, where at least either scenario shows a significant sensitivity. To obtain a measure relative to the actual (or irrigated when comparing irrigated and rainfed scenarios) scenario, the average difference values were divided with the average sensitivity magnitude of the actual (irrigated) scenario for the FPUs included. For each crop, to assess whether the mean sensitivity magnitude difference is statistically significantly different from zero, a distribution of the mean difference was created by calculating the average from bootstrapped (N = 1,000, with replacement) difference values of each FPU and oscillation. For the scenarios with varying fertilizer use set-up, we included only those nine GGCMs which have data for both 'fullharm' and 'harm-suffN' settings and also simulate nutrient stress, i.e. pDSSAT, EPIC-Boku, EPIC-IIASA, GEPIC, pAPSIM, PEGASUS, EPIC-TAMU, ORCHIDEE-crop, and PEPIC. Triple, double and single asterisks denote the confidence level at 99.9 %, 99 % and 90 %, respectively. Maps of sensitivity for each cropping system are shown in Figs S14-S18~~S9-S13~~ and difference in sensitivity magnitude in Figs S19-S23~~S14-S18~~. Please note different scale in x-axis between the columns.

4 Discussion

In this study, we inspected the historical relationship between crop yield variability and climate oscillations in a range of cropping systems by utilizing an ensemble of historical crop yield simulations generated in GGCMI. The results of this study highlight the widespread impacts that ENSO, IOD and NAO have on crop yields at the global scale, as well as potential options for mitigating their impacts.~~mitigation.~~ Further, we find robust impacts for these oscillations in many areas around the globe, e.g. in southern parts of Africa and northern South America for ENSO, and in eastern Australia for IOD, where these insights~~information~~ can potentially be utilized in efforts mitigating weather driven variations in crop productivity (Iizumi et al. 2018b).~~)~~

The reliability and usefulness of these results vary significantly between regions, crops and oscillations. In general, the teleconnections related to ENSO are the strongest, which is sensible, since ENSO has been shown to be the most significant driver of global climate variability (Dai et al. 1998, Trenberth 1997). Various institutions (including the United Nations) already provide action plans to mitigate ENSO's impacts on society. In Australia, there is significant potential to utilize the information of IOD along with ENSO, to understand crop yield fluctuations, as they can explain a large proportion of local crop yield variability (Fig. S13, Yuan and Yamagata 2015). Some promise also exists in using oscillation forecasts in predicting crop yield variability (Nobre et al. 2019). However, the quality of predictions of this type would naturally depend on the skill of the climate forecasts as well as the strength of the teleconnection. This study only provides a first assessment of correlations, and further work is needed before reliable forecasts can be provided.

Our results join existing research (Müller et al. 2018a~~2018~~, Schauberger et al. 2016, Okada et al., 2018) in highlighting the major role of irrigation in mitigating climate related crop yield variations, and thus securing global food production. This is an important point, since water supplies are highly stressed in many important crop-producing~~ production~~ areas (Kummu et al. 2016), which are also impacted by climate oscillations, such as parts of North America and South Asia. Thus, diminishing water resources could pose a major barrier in mitigating future negative impacts related to climate oscillations and climate variability in general. This can be very problematic, given that climate change will likely increase the occurrence of extreme weather in the future (Coumou and Robinson 2013). With given water shortages in some regions (Heinke et al. 2019), exploiting potentials to improve sustainable water use in agriculture (Jägermeyr et al. 2017) may thus be highly important for maintaining the long-term stability of the global crop production system. It~~However, it~~ should also be noted that there is substantial potential to improve water use efficiency with integrated crop water management measurements (Jägermeyr et al. 2016).

Interestingly, at the~~a~~ global level, increasing fertilizer use does not seem to decrease the sensitivity of crop yields to oscillations, potentially because low crop yield years remain the same while in years when conditions are suitable for crop growth, yields become even higher (Müller et al. 2018a~~2018~~), which would increase the sensitivity value as well. This explanation aligns with previous research, which has shown that increasing fertilizer use has limited potential to increase crop yields during years when weather conditions limit~~is not suitable for~~ crop growth (Liebig's law). In other words, additional fertilizer use in years with unfavourable seasonal climate condition does not lead to yield gain and is not cost effective, even if it is beneficial in normal conditions.~~.~~ Therefore, decision support systems which guide farmers about optimal fertilizer use under predicted growing season climate can be useful to avoid investments in fertilizers in bad years (Hayashi et al., 2018).

4.1 Limitations and way forward

The selection of the time windows for calculating the oscillation metric can have an impact on the spatial crop yield sensitivity footprint~~signature~~, as briefly illustrated in this study as well (Fig. 1, Fig. S7). Previously used approaches for identifying these relationships include e.g. looking at crop yield anomalies during the year (Heino et al. 2018, Iizumi et al. 2014, Yuan and Yamagata 2015) and years around (Anderson et al. 2017) strong oscillation anomalies. In these studies, strong oscillation anomalies are calculated either for the season in which~~that~~ the oscillations ~~shows the strongest signal~~ (Heino et al. 2018, Anderson et al. 2017, Yuan and Yamagata 2015) or the harvest season (Izumi et al. 2014) show the strongest signal.~~).~~ In general, it can be said that it is very difficult to find metrics for the oscillations that would work perfectly everywhere. A lack of accurate, spatially-detailed crop calendars makes addressing this issue particularly challenging. The justification for the methods used here is to look at how crop yields vary around~~during~~ the time, in which~~year after~~ these oscillations show their strongest signal, which can provide valuable information for early warning systems.

Future work could try to trace intermediate effects in order to explain the mechanisms at play, e.g.~~, e.g.~~ combining the effect of oscillations on weather, the effect of each aspect of weather on crop planting, development and harvest, and the final result in terms of crop yield. Such research could additionally provide useful information for decreasing crop yield variations~~variability~~, and thus increasing the resilience of crop production to climate variability.

The teleconnection patterns related to the IOD can be difficult to fully disentangle from ENSO due to their coevolution. Previous studies have shown that around 20 % to 45 % of IOD variability could be explained by ENSO depending on the data and the investigated time frame (Saji and Yamagata 2003, Zhang et al. 2015). The nature of this relationship is still debated (Hameed et al. 2018, Stuecker et al. 2017), and determining the influence of ENSO on the IOD and vice-versa is not in the scope of this study. However, through the use of multivariate ridge regression, we aim to filter the influence of ENSO from the IOD patterns. Also, the relationship between ENSO and NAO has been studied, but that relationship has been shown to be relatively weak (Hurrell et al. 2003).~~variation.~~

The data used here are from state of the art global gridded crop models included in phase 1 of the GGCMI of AgMIP. However, major uncertainties in the simulated crop yields still exist, and the relationships observed here between crop yields and these oscillations are often not consistent throughout the ensemble of crop models (see Fig. 3). Differences and uncertainties among the models arise e.g. from soil and crop type parametrisations as well as handling of water and nutrient stress (e.g. Folberth et al. 2019~~2016~~). Additionally, uncertainties in these GGCMs arise from the simulated cropping systems, as simulations assume~~have~~ only a single annual harvest per crop and per grid cell, whereas multiple harvests are common for e.g. rice. In general, simulated crop yields seem to be most reliable in high nutrient-input areas (Müller et al. 2017), where observed climate variability also explains~~explain~~ a majority of reported crop yield variation (Ray et al. 2015).

This study has included comparison with fully fertilized and irrigated management scenarios intended to capture (unattainable) ideal management, with no water or nutrient stress anywhere. This helps understand the physical potential of the management measures for mitigating crop yield variability related to these oscillations, according to the models used. In future, practical limitations could also be taken into account by limiting water and fertilizer use to locally available resources.

The three climate oscillations included here are only a share of the whole range of periodically fluctuating climatological phenomena that could impact crop growing conditions. Thus, studying the relationship between simulated crop yields and other climate oscillations, not included here, such as Scandinavian Pattern or the Arctic Oscillation, would provide additional insights to this topic, as demonstrated by a recent study by Ceglar et al. (2017).

5 Conclusions

This study strengthens the evidence that climate oscillations are drivers of crop yield variability around the world. In several areas, where these oscillations show robust impacts on crop production, e.g. Australia, southern Africa, as well as parts of North and South America, local risk reduction efforts~~disaster control~~ as well as global efforts can already benefit from utilizing these known relationships to improve the stakeholders' preparedness against ~~in mitigating~~ crop production shocks associated with the climate oscillations.~~against climatologically driven variations.~~ Information for maintaining the stability of global crop production is of high importance, given that anticipated climate change and population growth will keep increasing the pressure towards the global food system. Finally, our~~Finally, we want to highlight the importance of water in mitigating crop yield variability. Our~~ results suggest that increases (decreases) in the extent of irrigated area would, on average, reduce (amplify) the impacts of these oscillations on crop yields, which highlights the importance of ~~. Hence,~~ sustainable water use in~~is crucial for~~ maintaining the long-term stability of the global crop production system~~.~~

~~6~~ Code and data availability

The processing scripts are available from GitHub~~github~~: https://github.com/matheino/crops_and_oscillations. The simulated crop yield data were retrieved from the GGCMI data archive: http://www.rdcep.org/research-projects/ggcmi, and they are also available through the links provided in the references of Table 1.

~~7~~ Author contribution

M.H., J.H.A.G. and M.K. designed the research in consultation with C.M. and T.I. Analyses were conducted by M.H. supported by all co-authors. M.H. wrote the article, with contributions from all co-authors.

~~8~~ Competing interests

The authors declare no competing financial interests.

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