Interactive comment on "Agricultural management effects on mean and extreme temperature trends" *by* Aine M. Gormley-Gallagher et al.

Anonymous Referee #2

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The authors' summary statement in the abstract is certainly an informative conclusion. They write
"Our results underline that agricultural management has complex and nonnegligible impacts on the local climate and highlights the need to account for land management in climate projections."

And further that
"It remains challenging to resolve this, however, because it is difficult to separate land management from other effects in GCMs – particularly natural climate variability (Cook et al., 2015)".

The Reviewer's time is greatly appreciated and we believe that by addressing the Reviewer's comments as outlined below, it has enhanced the value and quality of the paper. A point-by-point response to each comment is detailed below and the amended manuscript text is provided in italics.

1. They summarize their paper with the text
   "The goal of this study is thus to test the hypothesis that CESM version 1.2.2 overestimates warming trends in some regions because irrigation and CA are excluded. That is, warming rates are hypothesised to decline – showing signs of cooling, in irrigation- and CA-affected regions when climate models do account for a theoretical constant level of these land management practices. To realise this goal, the following three objectives were formulated: (1) Determine spatial warming rates using GCM simulations that account for irrigation and CA and inspect whether CESM overestimates warming trends; (2) Compare the observed rates of warming to the modelled rates of warming for irrigated and CA pixels, as well as nonirrigated and non-CA pixels; and (3) Estimate the impact of irrigation on the spatial average of the warming rates over time (1981-2010) for all land, selected regions, and irrigated and CA pixels."

   However, the basis to quantify these impacts is flawed, or at least significantly muddled. First, model comparison studies are just model sensitivity studies. Without an assessment of model skill with the appropriate real world observed data, this is an incomplete (and potentially misleading) approach. The real world data needs to be on the spatial and temporal scale of the effect they are assessing (irrigation and conservation agriculture). The recent GRAINEX project quantified these scales [https://www.eol.ucar.edu/field_projects/grainex]. The model results should be compared against such data.

   Indeed there are numerous regional, mesoscale and local studies that have assessed the role of irrigation and land management on weather and climate. The authors do not seem to be familiar with this research. Here are just a few

   Adegoke, J.O., R.A. Pielke Sr., J. Eastman, R. Mahmood, and K.G. Hubbard, 2003: Impact of irrigation on midsummer surface fluxes and temperature under dry synoptic conditions: A regional atmospheric model study of the U.S. High Plains. Mon. Wea. Rev., 131, 556-564.

   Betts RA. Implications of land ecosystem-atmosphere interactions for strategies for climate change adaptation and mitigation. Tellus B 2007, 59:602–615. doi:10.1111/j.1600-0889.2007.00284.x.

   Boyaj et al, 2020: Increasing heavy rainfall events in south India due to changing land use and land cover. QJRMS https://doi.org/10.1002/qj.3826.

   Chen, C. J., C. C. Chen, M. H. Lo, J. Y. Juang, and C. M. Chang, 2020: Central Taiwan's hydroclimate in response to land use/cover change. *Env. Res. Lett.,* **15,** 034015

   Douglas, E.M., D. Niyogi, S. Frolking, J.B. Yeluripati, R. A. Pielke Sr., N. Niyogi, C.J. Vörösmarty, and U.C. Mohanty, 2006: Changes in moisture and energy fluxes due to agricultural land use and irrigation in the Indian Monsoon Belt. Geophys. Res. Letts, 33, doi:10.1029/2006GL026550.

   He, Y., E. Lee, and J. S. Mankin, 2019: Seasonal tropospheric cooling in Northeast China associated with cropland expansion. Env. Res. Lett. 15, 034032.

   Hossain, F., J. Arnold, E. Beighley, C. Brown, S. Burian, J. Chen, S. Madadgar, A. Mitra, D. Niyogi, R.A. Pielke Sr., V. Tidwell, and D. Wegner, 2015: Local-to-regional landscape drivers of extreme weather and climate: Implications for water infrastructure resilience. J. Hydrol. Eng., **10.1061/(ASCE)HE.1943- 5584.0001210** , 02515002.

   Pielke Sr., R.A., 2001: Influence of the spatial distribution of vegetation and soils on the prediction of cumulus convective rainfall. Rev. Geophys., 39, 151-177.

   Pielke Sr., R.A., R. Mahmood, and C. McAlpine, 2016: Land's complex role in climate change. Physics Today, 69(11), 40.

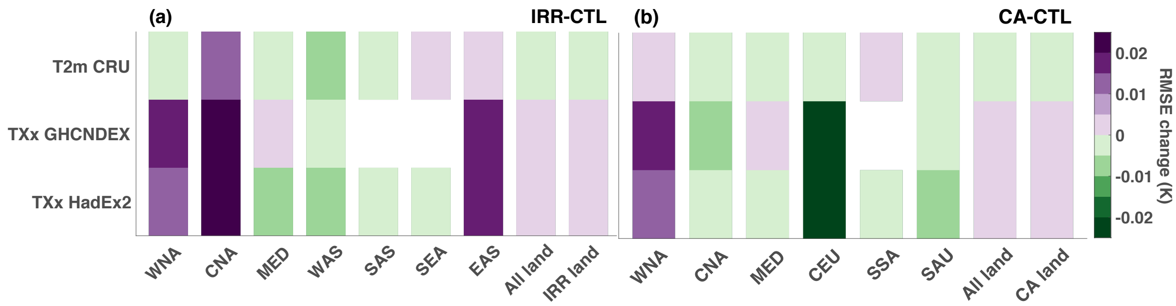
   Ullah et al 2020: How Vegetation Spatially Alters the Response of Precipitation and Air Temperature? Evidence from Pakistan. Asian Journal of Atmospheric Environment 14(2): 133- 145.

   Woldemichael, A.T., F. Hossain, and R. A. Pielke Sr., 2014: Impacts of post-dam land-use/land-cover changes

on modification of extreme precipitation in contrasting hydro-climate and terrain features. J. Hydrometeor., 15, 777–800, doi:10.1175/JHM-D-13-085.1.

Zhang, T., R. Mahmood, X. Lin, and R.A. Pielke Sr., 2019: Irrigation impacts on minimum and maximum surface moist enthalpy in the Central Great Plains of the USA. Weather and Climate Extremes, 23, https://doi.org/10.1016/j.wace.2019.100197.

Reply. Thank you for raising these important points. We firstly wish to highlight that our work is not merely a model sensitivity study, as we compare our simulations against three observational products (see Figure 2 and Table 1 in the paper). Figure 2 has now been updated (shown below as 'Response Figure 1') to display the absolute change in spatial root-mean-square error for the IRR and CA ensemble relative to the CTL ensemble over different regions and with respect to 3 observational products. The paper's Table 1 details the bias and spatial RMSE of the ensemble mean warming trends of the CTL, IRR and CA experiments versus the observational products. We do however agree that including additional observational products for comparison at the subgrid scale would improve the completeness of the approach. The products recommended by the Reviewer are appreciated, but given the global scope of our analysis as well as the focus on trends; we feel that the spatial and temporal coverage of this data is inadequate for validation of global model outputs. To resolve this and address the Reviewer's point, we have added an analysis of the E-OBS European CDG data. Please see our response to Reviewer point 3 below for full details regarding this additional analysis.



Response Figure 1. *Added value of including irrigation and CA in the simulated warming trends over 1981-2010. Absolute change in spatial root-mean-square error (RMSE) for the (a) IRR and (b) CA ensemble relative to the CTL ensemble over different regions (x axis) and with respect to 3 observational products (y axis). Considered regions are the SREX regions where irrigation is extensive (as highlighted in the paper's Figure 1a) and where CA is extensive (see Figure 1b of the paper), in addition to global land, global irrigated land and global CA land. Observational products are for near-surface air temperature* T_{2m} *(CRU), annual maximum daytime temperature TXx (GHCNDEX and HadEX2). The spatial RMSEs are computed for the ensemble mean warming trend in every pixel, and subsequently averaged over the selected region. Regions with an observational coverage below 50% are marked in white.*

We also agree as to the benefits of including more local studies that have assessed the role of irrigation and land management on weather and climate. Thus, the introduction has been substantially reworked to now read as follows:

"Conservation agriculture (CA), which involves crop residue management, crop rotation (Carrer et al., 2018; Lombardozzi et al., 2018) and minimal or no tillage (Kassam et al., 2015), can create climate feedbacks due to the presence of a crop residue over CA land change both the radiative and hydrological properties at the surface (Davin et al., 2014). Hirsch et al. (2018) explored whether applying the no-till component of CA within the Community Earth System Model (CESM) improves the simulation of present-day climate. They found that the surface temperature response was influenced by three competing effects: (1) a surface albedo increase – which reduces the availability of energy for partitioning between the sensible and latent heat fluxes; (2) increased surface resistance (e.g. from mulch) – which reduces soil evaporation; and (3) increased soil moisture retention leading to enhanced transpiration. The local cooling response to CA was somewhat counteracted by grid-scale changes in climate over North America, Europe, and Asia because of negative atmospheric feedbacks. That is, the decrease in evapotranspiration (ET) – both due to higher albedo and higher soil resistance – appeared to activate a decrease in cloud cover in the model that increases incoming shortwave radiation and therefore temperature via enhanced sensible heating. Grid-scale changes in climate counteracting local responses to land use change has also been demonstrated by Malyshev et al. (2015) who showed that the subgrid signal of land use change in near surface temperature was diminished by the averaging with undisturbed portions of the grid cells. The importance of local-scale responses to land cover change has also been indicated in observation-based studies (e.g., Mahmood et al., 2013; Li et al., 2016), yet few global-scale modelling studies examine the local land surface response to land management (Paulot et al., 2018; Meier et al., 2018).

Using GCMs, such as CESM, to simulate land-atmosphere interactions for investigating the effects of irrigation and agricultural conversion has been criticized as insufficient (Niyogi et al., 2002). This is partly because their coarse resolution (e.g. of order 100 km) hampers their performances in describing the present-day climate at the regional scale (Jiang et al., 2016). Furthermore, economic, societal and water resource factors are ignored – a void that initiated the so-called 'bottom-up' approach to evaluating the effects of land-use change (Douglas et al., 2006).

Regarding the applicability of the knowledge produced by GCMs, they do not provide the skill required at the spatial scale to offer practical responses at the infrastructure scale (Hossain et al., 2015). Despite these constraints, GCMs remain a prime tool for projecting changes in the climate system (Fajardo et al., 2020; Gupta et al., 2020; Hofer et al., 2020). Examples include the GCMs that are part of the latest Coupled Model Intercomparison Project (CMIP6) and used by the IPCC in consecutive assessment reports (Yazdandoost et al., 2020). However, these GCMs largely exclude agricultural management. In particular, no CMIP5 model incorporates irrigation or CA and only three CMIP6 models include irrigation, while none have CA. Pielke et al. (2011) suggested that landscape change is omitted from the CMIP5 models because the direct radiative impact of global landscape is a lower order than the radiative forcing from greenhouse gas emissions. This constitutes a reason to investigate their inclusion. That is, to distinguish between the effects of land management and other large-scale forcings such as a doubling of CO_2 *(Schultz et al., 2016), it is important to evaluate these processes in the GCMs and ultimately gain insight into the contrasts of impacts between regions under different climate regimes.*

Considering the potential effects of irrigation and CA on climate (Thiery et al., 2017), it is possible that the discrepancies between climate models and observations regarding temperature changes (Donat et al., 2017) are because the models exclude the effect of agricultural management techniques on temperature. The goal of this study is thus to test the hypothesis that CESM version 1.2.2 overestimates warming trends in some regions because irrigation and CA are excluded. That is, warming rates are hypothesized to increase at a slower rate – showing signs of cooling, in irrigation- and CA-affected regions when climate models do account for a theoretical constant level of these land management practices. To realise this goal, the following objectives were formulated: (1) Determine spatial warming rates using simulations that account for irrigation and CA and inspect whether CESM overestimates warming trends; (2) Compare the observed rates of warming to the modelled rates of warming for irrigated and CA pixels, as well as non-irrigated and non-CA pixels; and (3) Estimate the impact of irrigation on the spatial average of the warming rates over time for all land, selected regions, and irrigated and CA pixels."

2. Unfortunately, the study does not have fine enough spatial resolution to realistically resolve these land use effects. As a result, the effects will likely be muted and quite possibly misrepresented. Even examining sub pixel (grid interval) model data is insufficient as local and mesoscale effects are missed.
   As they report
   "The period 1976-2010 was simulated with a horizontal pixel resolution of 0.9° latitude × 1.25° longitude."
   This is much too coarse. Indeed since at least 4 grid increments are required to have some confidence that a feature is adequately resolved, their effective resolution is no finer than 3.6° latitude by 5° longitude.
   Similarly, their observational analyses used to evaluate the model results are too coarse. They write
   "For evaluation purposes, observational datasets for annual mean T2m with a spatial resolution of 0.5◦ × 0.5◦ for the same time period were obtained from the Climate Research Unit (CRU) (Harris et al., 2014). Annual mean TXx observational datasets were obtained from the daily Global Historical Climatology Network extremes data set (GHCNDEX) (Donat et al., 2013a) and the Hadley Centre extremes data set (HadEX2) (Donat et al., 2013b) with a spatial resolution of 2.5◦ × 2.5◦ "

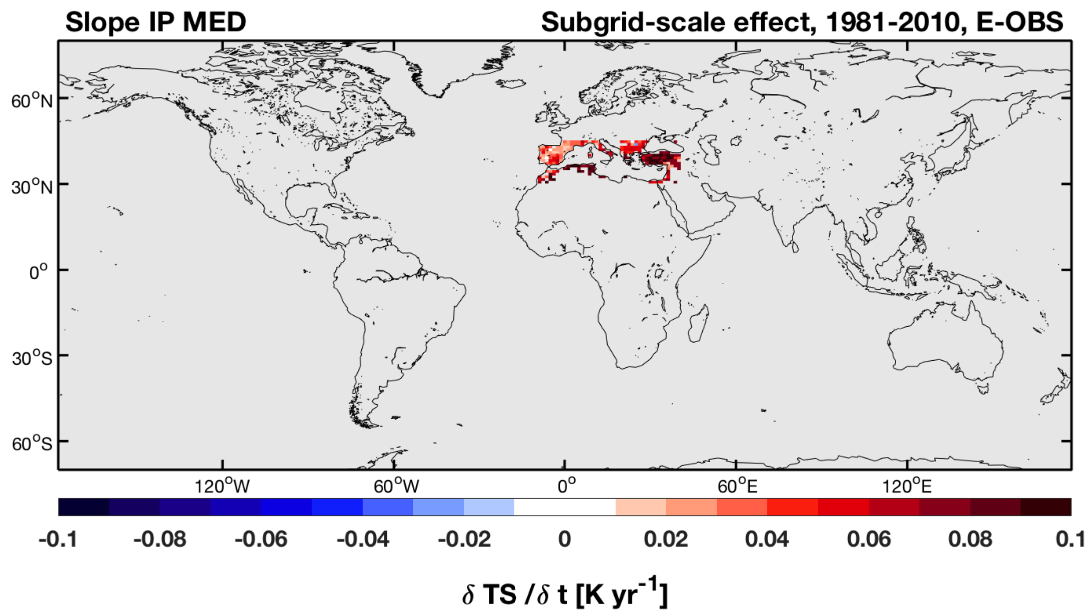
Reply. An underlying premise of this paper is that GCMs remain the primary tool for providing long-term projected changes in the climate system and have been often used for studying land cover and land management effects on climate. Unfortunately there currently is no global model that can be run for long integrations at the spatial resolution required to fully resolve field-scale land management variations including contrasts of the irrigation/CA impact between regions under different climate regimes. So while we acknowledge that the effects play out more at the local scale and are therefore better captured with high-resolution RCMs, we believe it is still relevant to also evaluate these processes in the GCMs. To resolve this (and in combination with addressing Reviewer's point 1), we elaborate on the RCM literature and include a justification of using a GCM in the revised introduction, as follows (also detailed in paragraph 2 of our response to the Reviewer's point 1):

"Using GCMs, such as CESM, to simulate land-atmosphere interactions for investigating the effects of irrigation and agricultural conversion has been criticized as insufficient (Niyogi et al., 2002). This is partly because their coarse resolution (e.g. of order 100 km) limits their ability to resolve land surface heterogeneity at the regional scale (Jiang et al., 2016). Furthermore, economic, societal and water resource factors are ignored – a void that initiated the so-called 'bottom-up' approach to evaluating the effects of land-use change (Douglas et al., 2006). Regarding the applicability of the knowledge produced by GCMs, they do not provide the skill required at the spatial scale to offer practical responses at the infrastructure scale (Hossain et al., 2015). Despite these constraints, GCMs remain a prime tool for projecting changes in the climate system (Fajardo et al., 2020; Gupta et al., 2020; Hofer et al., 2020). Examples include the GCMs that are part of the latest Coupled Model Intercomparison Project (CMIP6) and used by the IPCC in consecutive assessment reports (Yazdandoost et al., 2020). However, these GCMs largely exclude agricultural management. In particular, no CMIP5 model incorporates irrigation or CA and only three CMIP6 models include irrigation, while none have CA. Pielke et al. (2011) suggested that landscape change is omitted from the CMIP5 models because the direct radiative impact of global landscape is a lower order than the radiative forcing from greenhouse gas emissions. This constitutes a reason to investigate their inclusion. That is, to distinguish between the effects of land management and other large-scale forcings such as a doubling of CO_2

(Schultz et al., 2016), it is important to evaluate these processes in the GCMs and ultimately gain insight into the contrasts of impacts between regions under different climate regimes."

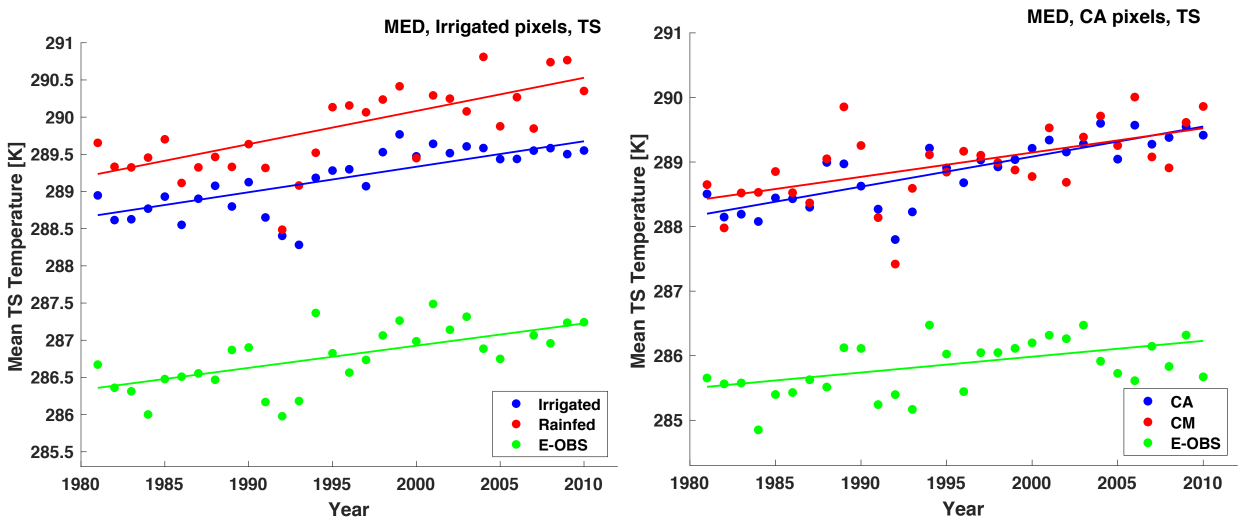
3. And, as I mentioned above, even using sub-grid decomposition is significantly incomplete. They write
"To examine heterogeneous influences within grid cells, subgrid tiles that represent local physical, biogeochemical, and ecological characteristics – and therefore local (subgrid) influences of irrigation and CA – were evaluated against regional (grid-scale) influences. Up to 21 surface tiles may occur within one grid cell in CLM4, including glacier, wetland, lake, urban, bare soil and 16 PFTs."
While useful in a model sensitivity study, its lack of connection to real world data for locations where actual irrigation and conservation agriculture are occurring is a serious oversight.
In their recommendations they write
"The findings overall emphasise the need for a more in-depth evaluation of the sensitivity of future climate projections to irrigation and CA-induced temperature changes. A sensitivity analysis, using transient irrigation and CA extents, as well as additional land management techniques and climate models based on CMIP6 output, , is recommended."
I agree with the first sentence. The second sentence, however, is incomplete as a necessary condition. Real world testing of the skill of the models with respect to how land management affects the weather and climate is required. This must be completed using real world data that is on the appropriate space and time scales. This is not the case for this paper.

Reply. Thank you for raising this important point. As noted under point 1, our work goes beyond that of a model sensitivity study, as we compare our simulations against three observational products, but indeed none at the subgrid scale. We have therefore used real world data from the E-OBS European CDG dataset to conduct additional analysis. As a regional data set, it has a higher spatial resolution and therefore allows us to test the skill of the models with respect to the local effects of land management. The E-OBS data was regridded to the CESM resolution using bilinear remapping for use in this study. It captures well the MED SREX region used in this study. Please see Response Figure 2 below for the surface radiative temperature (TS) slope results over irrigated pixels (NB: this chart will not be in the revised paper but is included here to visually introduce the new observation dataset used).



Response Figure 2. *The warming trends of surface radiative temperature (TS) for the MED SREX region over irrigated pixels based on the E-OBS European CDG dataset for the period 1981-2010.*

Below are the (spatial) average of the (TS) warming rates for the MED region over (left) irrigated pixels for the irrigated and rainfed crop tiles; (right) CA pixels for the CA and CM crop tiles. Note here the slope bias has improved with the irrigated crop tile data (versus the rainfed) – see table below for data. Both of these charts have been added to Figure 7 in the paper.



Response Figure 3*. Average of the TS warming rates over (left) irrigated pixels for the irrigated and rainfed crop tiles; (right) CA pixels for the CA and CM crop tiles. Data points specify the mean TS values within the crop tiles and pixels specified. The slope was estimated using Sen's slope for the rainfed/CM (red), irrigated/CA (blue) experiments, as well as the E-OBS European CDG dataset (green).*

The table below contains the bias and spatial RMSE of the slopes versus the E-OBS product. These results have been added to the paper as Table 3, as well as the following description and interpretation of the results. For the subgrid irrigation (IRR_{SUB}) ensemble, TS warming trends are overestimated by ~0.004 K yr^{-1} across irrigated MED pixels, which is an improvement in terms of bias when compared to the subgrid data that does not account for irrigation (i.e. RAIN). However, according to the change in the spatial RMSE, accounting for irrigation does not improve the simulation skill for trends over MED irrigated pixels. This is likely because RMSE is more sensitive to outliers – whereas the bias is based on the spatial mean.

Response Table 1*. Bias and Spatial RMSE of the Ensemble Mean Warming Trends (Slopes) of the RAIN, IRR_{SUB}, CA_{SUB} and CM Experiments Versus the E-OBS (K yr^{-1}) Observational Product for the years 1981-2010.*

Irrigated MED pixels bias		**CA MED pixels bias**		**Irrigated MED pixels RMSE**		**CA MED pixels RMSE**	
RAIN	IRR_{SUB}	CM	CA_{SUB}	RAIN	IRR_{SUB}	CM	CA_{SUB}
0.015	0.004	0.013	0.022	0.028	0.031	0.027	0.026

4. They also write

"This will support decision-making when planning land management strategies that combine resource use efficiency with climate change adaptation and mitigation, enabling sustainable intensification of land management to meet mitigation targets and future demand for food, fuel, fibre, and water."

The authors should be made aware that there are much more inclusive tools to assess sustainability. Sensitivity results from global models is, at best, a small part on the regional and local scales. Examples of such an approach are published in

Cross, M. S., et al. (2012). "The Adaptation for Conservation Targets (ACT) framework: a tool for incorporating climate change into natural resource management." Environmental Management 50(3): 341-351. DOI: 10.1007/s00267-012-9893-7.

Hanamean, J.R. Jr., R.A. Pielke Sr., C.L. Castro, D.S. Ojima, B.C. Reed, and Z. Gao, 2003: Vegetation impacts on maximum and minimum temperatures in northeast Colorado. Meteorological Applications, 10, 203-215.

Hossain, F., E. Beighley, S. Burian, J. Chen, A. Mitra, D. Niyogi, R.A. Pielke Sr., and D. Wegner, 2017: Review approaches and recommendations for improving resilience of water management infrastructure: The case for large dams. J. Infrastructure Systems, 23, Issue 4, Dec. 2017, DOI: 10.1061/(ASCE)IS.1943-555X.0000370.

Kittel, T.G.F., et al. (2011). "A vulnerability-based strategy for incorporating climate change in regional conservation planning: Framework and case study for the British Columbia Central Interior." BC Journal of Ecosystems and Management 12(1): 7-35. http://jem.forrex.org/index.php/jem/article/view/89.

Kittel, T.G.F. 2013. "The Vulnerability of Biodiversity to Rapid Climate Change." Pp. 185-201 (Chapter 4.15), in: Vulnerability of Ecosystems to Climate, T.R. Seastedt and K. Suding (Eds.), Vol. 4 in: Climate Vulnerability: Understanding and Addressing Threats to Essential Resources, R.A. Pielke, Sr. (Editor-in-

Chief). Elsevier Inc., Academic Press, Oxford. DOI: 10.1016/B978-0-12-384703-4.00437-8

Kling, M. M., Auer, S. L., Comer, P. J., Ackerly, D. D., & Hamilton, H. (2020). Multiple axes of ecological vulnerability to climate change. Global Change Biology, 26, 2798–2813

Ordonez, A., 2020. Points of view matter when assessing biodiversity vulnerability to environmental changes. *Global Change Biology*, *26*(5), pp.2734-2736.

Pielke Sr., R.A., R. Wilby, D. Niyogi, F. Hossain, K. Dairaku, J. Adegoke, G. Kallos, T. Seastedt, and K. Suding, 2012: Dealing with complexity and extreme events using a bottom-up, resource-based vulnerability perspective. Extreme Events and Natural Hazards: The Complexity Perspective Geophysical Monograph Series 196 © 2012. American Geophysical Union. All Rights Reserved. 10.1029/2011GM001086.

Romero-Lankao, P., et al. 2012: Vulnerability to temperature-related hazards: a meta-analysis and meta-knowledge approach. Glob. Environ. Change, http:// dx.doi.org/10.1016/j.gloenvcha.2012.04.002.

Stohlgren, T.J. and C.S. Jarnevich. 2009. Risk assessment of invasive species. In: M.N. Clout and P.A. Williams (eds.). Invasive Species Management: A Handbook of Principles and Techniques. New York: Oxford University Press. p. 19-35.

Reply. We believe that the inclusion of other tools to assess sustainability, such as the ACT framework example provided above is beyond the scope of this study and would detract from its unity. However, we do concur that the final sentence in the paper, referred to by the reviewer above, was too sweeping, and thus the final paragraph has been amended to read:

> *"The findings overall provide valuable context on how model complexity can impact the simulation of trends and emphasise the need for a more in-depth evaluation of the sensitivity of future climate projections to irrigation and CA-induced temperature changes. A sensitivity analysis, using transient irrigation and CA extents, as well as additional land management techniques, within coupled climate models based on CMIP6 output, is recommended. In this way, the variance can be approximated and the relative contributions of the uncertainty sources to the total uncertainty in the model output, as well as the relative importance of irrigation and CA to the total warming trends, can be quantified and compared. If the fundamental uncertainties relating to model structure dominate, then a more detailed analysis than the regression approach used in this study is suggested. This will support decision-making on the incorporation of agricultural management processes in future GCM projects."*

5. Thus, while I am pleased to see a study examining the effects of irrigation and conservation agriculture on climate, the study has significant shortcomings as summarized in this review.

Reply. Thank you for your time and effort on our paper and for raising important points. We believe our resolve of these points has helped to improve our paper, which is much appreciated.