Response to Reviewer 1

General comment

The combined effect of drought and salinity on crops is very important for food security under global change background. Remote sensing shows its advantage for large-scale applications. This paper used the sentinel-2 satellite data to conduct an analysis in this regard. The findings are interesting.

Response: Thank you for your positive comments of our work. We appreciate that our work provides insights into monitoring drought and salinity impacts on crops by remote sensing on a large scale. Our itemized responses are attached below. In order to facilitate the review, the comment of the reviewer is displayed in black, and the reply is displayed in blue font.

Major concerns

Q1. Irrigation can mitigate the drought effect to a large extent. I would like to know how irrigation has influenced the analysis. There is no information reported in this regard.

Response: We agree that irrigation plays an important role in relieving drought impacts on crops in many cases. In this study, we have evidence that irrigation did not play a major role in the patterns found. First of all, all croplands included within our research area have been identified as rainfed cropland (see Fig. 1 below) according to the ESA/CCI land cover map in 2018 (https://maps.elie.ucl.ac.be/CCI/viewer/). In addition, while -in the area- farmers are known to irrigate their cropland, the Dutch government announced a temporary national irrigation ban in various areas including our research area in 2018 (Perry de Louw, 2020) to spare water. Therefore, we assumed that irrigation management was absent during our study period. We agree that in other cases, irrigation may modify several of the patterns found and we will add a remark on this to the discussion section of the revised manuscript.

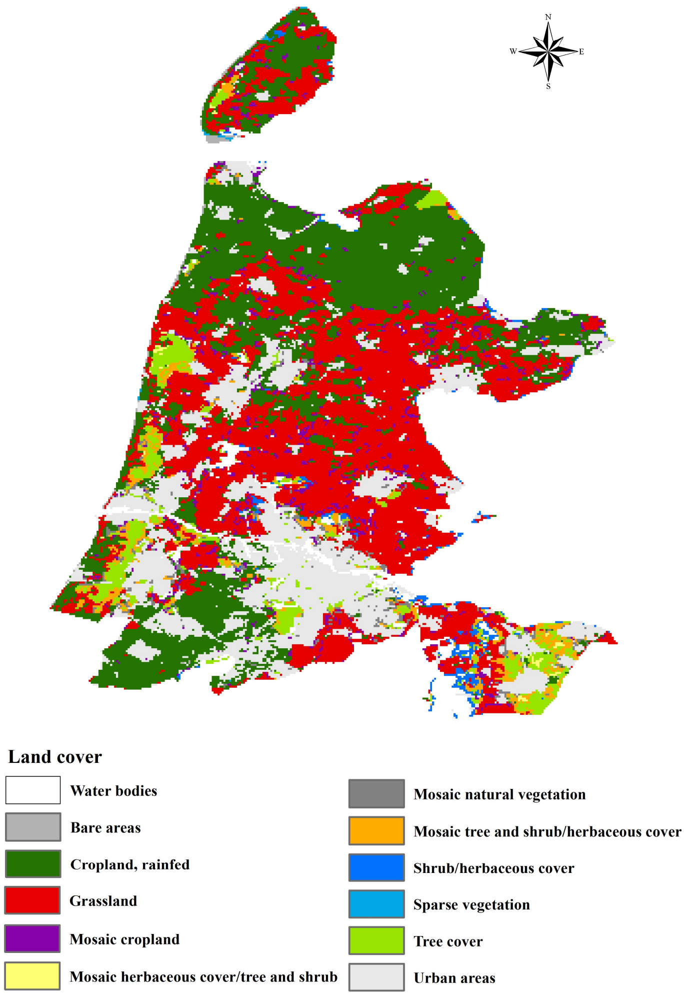

Fig. 1 The land cover map of North-Holland

Q2. Five different indicators were used to depict the health condition of different crops. I am wondering how the stress factors influence the final yield. Is it possible to have some discussion in this regard.

Response: Yield information is not available at pixel level but only at farm level in the Netherlands. Particularly, given the average size of a farm, such information is not insightful at the scale with which we are working. Moreover, there are no yield products available based on remote sensing at such high resolution. Therefore, we cannot directly derive yield estimates from remote sensing and we used these five crop traits instead to understand crop responses. Traits including Cab, LAI, and FAPAR, have been used (either separately or in combination) as proxy for final yield estimates from remote sensing in many studies. For instance, the Normalized Difference Vegetation Index (NDVI) which is based on the combination of LAI and Cab, is extensively used to estimate crop yield (Huang et al., 2014;Mkhabela et al., 2011;Vannoppen et al., 2020). Also LAI itself has been used for predicting final yield (Sun et al., 2017;Dente et al., 2008;Doraiswamy et al., 2005). Meanwhile, Cab and FAPAR were also proven to be highly correlated with crop yield (López-Lozano et al., 2015;Ghimire et al., 2015). Thus, while yield cannot be estimated directly from remote sensing or ground truth data at the desired high spatial resolution, our indicators do relate to yield and can be used in more application-based contexts to inform on yield impacts. In our revised manuscript, we will highlight these relationships with the final yield to make the link to wider application of our findings.

Minor comments

Q3. Line 33, more deeply challenged.

Response: We will revise “deeper challenged” to “more deeply challenged”.

Q4. Line 37, delete ‘of’ and ‘more than’

Response: We will delete ‘of’ and ‘more than’ from this sentence.

Q5. Lines 83-90, why was SPEI selected as the drought indicator rather than the others? What is the RD_new projection? Where are the precipitation and PET data from?

Response: There are several common drought indices including the Palmer Drought Severity Index (PDSI), the Standardized Precipitation Index (SPI), the Standardised Precipitation-Evapotranspiration Index (SPEI), etc., to evaluate drought events. PDSI, which is based on the water balance equation, has disadvantages due to autoregressive characteristics and its fixed temporal scale (Guttman, 1998). SPI, which is calculated from precipitation data, shows better performance than PDSI on droughts detection thanks to its multi-scalar features (Hayes et al., 1999). Nevertheless, compared with these two common drought indices, the SPEI is a multiscale drought index based on precipitation and temperature data, and in this way, it has the advantage of detecting, monitoring, and assessing drought in multiple systems (Vicente-Serrano et al., 2010).

RD_new (EPSG:28992) projection is a projected coordinate reference system of the Netherlands. All maps were projected to RD_new projection to create consistent data layers. We will explain this in the revised manuscript.

The drought map was created by our group, and published in another study in the journal Science of the Total Environment (Chen et al., 2022). The precipitation data were fused based on remote sensing data and ground observations. The PET data was obtained from MODIS in 8-day composite dataset. More details can be found in Chen et al. (2022).

Q6. Lines 124-129, Include some information about Sentinel-2 in the data description although it was pointed out in Fig. 1.

Response: The following information about Sentinel-2 will be added to the revised manuscript:

The Sentinel-2 mission consists of two satellites equipped with high-resolution Multispectral Instrument (MSI) in the same orbit. The satellites acquire 13 spectral bands from the visible spectrum to the short-wavelength infrared spectrum in 5 days revisit times at a spatial resolution of 10m, 20m, and 60m (ESA, 2015). In our study, we used the 10m resolution as the SNAP toolbox requires both optical and near-infrared observations to be available for determining the functional traits. Bands in 20m including B5, B6, B7, B8A, B11 and B12 were resampled to 10m resolution to match consistency with B3 and B4.

Q7. Line 145, why was the biomass effect removed? Is this contradictory to the Cab*LAI and Cw*LAI at Line 142?

Response: In order to use truly independent variables within our analysis, we removed the biomass effect: SNAP uses a neural network to derive five canopy traits, namely LAI, FAPAR, FVC, canopy chlorophyll content (CCC), and canopy water content (CWC) (lines 141-142). However, these canopy traits are internally (in SNAP) calculated as (Cab*LAI) and (Cw*LAI), i.e. based on their leaf equivalents, Cab and Cw. Since both CCC and CWC are calculated from LAI, we divided them by LAI to obtain their leaf counterparts (Cw and Cab) to create fully independent variables. Thus, with the removal of the biomass effect, we mean the removal of the effects of LAI –which is also calculated separately within SNAP- from our functional trait estimates. We will modify the text to clarify this.

Q8. Line 151, What do you mean by 'due to the unbalance in the occurrence of stress conditions'?

Response: The unbalance in the occurrence of stress conditions means that the pixel counts of the six classes of stress combinations namely no stress, MD, SD, salinity (MS+SS), MD+MS, and MD+SS were (strongly) different. We will clarify this in the revised manuscript.

Q9. Lines 163-173, More explanations are needed to illustrate the connotations of different indicators in the ANOVA analysis, to increase the readability. Probably this can be supplemented in the methodology section.

Response: We will add the following information on the different indicators in the notes of Table 1 to make it more clear for readers**:**

Notes: *F* indicates the test statistic of the F-test; *p* indicates whether the effect is statistically significant in comparison to the significance level ($p < 0.05$); Partial Eta Squared indicates the effect size of different factors; R^2 indicates the percentage that the model coincides with the data.

Q10. Line 200, Add some information for the different letters indicating the significance level.

Response: All the significance levels are < 0.05 in Fig. 3 and Fig. 4. The letters in Fig. 3 and Fig. 4 indicate whether there is a significant difference among different stress groups based on the pairwise comparison. If the letter in one group is different from the other group, then a significant difference exists between these two groups. We'd like to clarify that it is a common way to show significant differences in bar plots throughout scientific literature as we have explained with the sentence 'Different letters in each panel indicate significant differences ($p < 0.05$)' in the caption.

Q11. Line 220 and Line 244, It was concluded at Line 220 that there is no additive effect for drought and salinity. Is it in contradiction to the severe effect of the co-occurrence of drought and salinity?

Response: In fact, these two points are not contradicting. The effects of two factors can be either additive or interactive. If two factors are additive, then the effect of both factors (in this case drought and salinity) equals the sum of the effects of the individual factors. Thus, the reduction in a trait value by the combination of drought and salinity would equal the reduction due to drought plus the reduction due to salinity. If the effects of two factors are interactive, then the combined effect of two co-occurring factors does not equal the sum of the individual effects. That was the case here in which we found that particularly the MD+SS conditions led to major impacts on our functional traits. We will revise our statements to make this distinction clear.

Q12. Line 257, why was the drought effect mitigated? Please add more explanations.

Response: More explanations will be added to the revised manuscript as follows:

Water stress impacts on photosynthesis and biomass of plants were extenuated by salinity since salinity enhances the synthesis of ATP and NADPH by promoting photosynthetic pigments and photosystem II efficiency. The impacts of combined drought and salinity stress on plant growth, chlorophyll content, water use efficiency, and photosynthesis were less severe compared to drought alone. This indicates the compensating effects on carbon assimilation due to osmotic adjustments induced by Na^+ and Cl^- (Hussain et al., 2020). Thus, the detrimental effect of single drought stress on crop growth is considered to be mitigated by salinity.

Q13. Line 278, 'Considering the additional', remove the comma. Change 'promising' to 'probable'.

Response: We will delete ',' and change 'promising' to 'probable'.

Q14. Line 283, 'In addition to facilitating the evaluation…'

Response: We will change 'being able to evaluate' to 'facilitating the evaluation'.

Q15. Line 285, distinctively

Response: We will revise this sentence to make it easier to understand. This sentence will be revised to: 'In our study, Cab and Cw responses to drought and salinity were distinct from responses of LAI, FAPAR, and FVC (Fig. 3 and Fig. 4).'.

Q16. Line 288, understand

Response: We will revise this sentence to: 'Given that individual crop traits may differently respond to drought and salinity, reflecting their stress resistance and tolerance strategies, the evaluation of these distinct responses may help to understand these strategies.'.

Q17. Line 289, as compared to

Response: We will revise this sentence to: 'In this study, Cw was consistently lower in all drought and salinity treatments as compared to no stress conditions in May, June and July.'.

Q18. Line 291, In this respect

Response: We will revise 'that' to 'this' in the sentence.

Q19. Line 292, the transpiration demand normally refers to the atmospheric demand, like VPD and incoming radiation. What do you mean here?

Response: Here transpiration means the loss of leaf water vapor.

Q20. Please check the English writing more carefully to enhance the readability.

Response: We will carefully revise the manuscript in terms of English writing to improve the readability.

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