RESPONSE TO REVIEWER #2 (Veit Blauhut)

We would like to thank Veit for taking the time to review our manuscript and for providing insightful and constructive comments, which have contributed to strengthen our manuscript.

Below is a point-by-point response to all comments. Original comments are in black, whereas the authors' responses are in blue.

Dear authors,

First of all I have to apologise for the strong delay in reviewing your paper. Overall it was a pleasure to review your excellent paper. Very well written and designed in a carefully thought-out way. I believe this study to be essential to support agricultural drought management in the future.

Thank you very much for your positive feedback and kind words regarding our manuscript. We appreciate the time and effort you have invested in reviewing our work, and we understand that the delay in the review process can be unavoidable. We are grateful for your thorough evaluation of our study and for recognising its significance in supporting agricultural drought management. Once again, thank you for your valuable contribution to our research.

In addition to the comments of SJ Sutantos comments there is only few to add on. All over I recommend this manuscript to be published after minor revisions.

I would appreciate if you could add some introductionary thoughts on the usage of the vegetation indices and their classification it they are rather used a drought index or as a proxy for impacts/ impacts. Also, if VHI can be used without any knowledge on the hazard situation?

Thank you for drawing our attention to the need for introductory thoughts on vegetation indices in our manuscript. We agree that this was missing, and in response, we will include the following text in our introduction on the usage of vegetation indices in the revised manuscript. We will remove any duplicate information from the Data section (2.2).

Vegetation indices derived from remote sensing are commonly used to monitor the impacts of drought on vegetation. The Normalised Difference Vegetation Index (NDVI) is one of the most established and widely used vegetation indices (Tucker, 1979). It exploits the sharp increase in vegetation reflectance across the red and near-infrared (NIR) regions of the electromagnetic spectrum, known as the 'red-edge', to detect photosynthetically active plant material and infer plant stress. However, the Vegetation Condition Index (VCI), a pixel-based normalization of NDVI, offers a more robust indicator for seasonal droughts by minimising spurious or short-term signals and *amplifying long-term trends (Anyamba and Tucker, 2012; Liu and Kogan, 1996). VCI has been widely used and has proved to be effective in monitoring vegetation change and signalling agricultural drought (e.g., Jiao et al., 2016). The Vegetation Health Index (VHI) is a composite index that combines the VCI and Temperature Condition Index (TCI) and is also commonly used to monitor vegetation stress and drought conditions (Kogan, 1997). VHI incorporates the effect of temperature and is therefore more suitable for monitoring the effect of drought in species more sensitive to concurrent heat stress. VHI has been successfully used worldwide to monitor vegetation stress and drought conditions (e.g., Jain et al., 2009; Singh et al., 2003; Unganai and Kogan, 1998). Note that these vegetation indices are relative indices that compare current conditions to the long-term average to measure vegetation health, and their interpretation depend on the environmental and climatic conditions of the study area. Therefore, it should be used in conjunction with information on the drought hazard situation to distinguish between drought and different hazards on vegetation (e.g. disease, floods, anthropogenic impacts).*

Besides their use as drought indicators, vegetation indices are often used as proxies for agricultural drought impacts. The relationship between crop yield and vegetation indices varies by crop type and location but has been shown to be strong in many locations. For example, strong correlations were found between vegetation indices and crop yield in North America (e.g., winter wheat, sorghum, and corn in Kogan et al., 2012; maize in Bolton et al., 2013), South America (e.g., white oat in Brazil in Coelho et al., 2020), Europe (e.g., maize in Germany in Bachmair et al., 2018 and cereals in Spain in Garcia-Leon et al., 2019), Asia (e.g., sugarcane in India in Dubey et al., 2018), the Middle East (e.g., paddy rice in Iran in Esfandabadi et al., 2022), Africa (e.g., millet and sorghum in the Sahelian region in Maselli et al., 2000), and Australia (e.g., wheat in Smith et al., 1995).

References:

Anyamba, A. and C.J. Tucker, Historical perspectives on AVHRR NDVI and vegetation drought monitoring. B.D. Wardlow, M.C. Anderson, J.P. Verdin (Eds.), Remote Sensing of Drought: Innovative Monitoring Approaches, CRC Press, New York, United States of America, 2012: p. 23-51. DOI: 10.1201/b11863.

Bachmair, S., M. Tanguy, J. Hannaford and K. Stahl, How well do meteorological indicators represent agricultural and forest drought across Europe? Environmental Research Letters, 2018. 13(3): p. 034042. DOI: 10.1088/1748-9326/aaafda.

Bolton, D.K. and M.A. Friedl, Forecasting crop yield using remotely sensed vegetation indices and crop phenology metrics. Agricultural and Forest Meteorology, 2013. 173: p. 74-84. DOI: https://doi.org/10.1016/j.agrformet.2013.01.007.

Coelho, A.P., R.T. de Faria, F.T. Leal, J.d.A. Barbosa and D.L. Rosalen, Validation of white oat yield estimation models using vegetation indices. Basic areas, Bragantia 79 (2), 2020. DOI: 10.1590/1678-4499.20190387.

Dubey, S.K., A.S. Gavli, S.K. Yadav, S. Sehgal and S.S. Ray, Remote Sensing-Based Yield Forecasting for Sugarcane (Saccharum officinarum L.) Crop in India. Journal of the Indian Society of Remote Sensing, 2018. 46(11): p. 1823-1833. DOI: 10.1007/s12524-018-0839-2.

Esfandabadi, H.S., M.G. Asl, Z.S. Esfandabadi, S. Gautam and M. Ranjbari, Drought assessment in paddy rice fields using remote sensing technology towards achieving food security and SDG2. British Food Journal, 2022. 124(12): p. 4219-4233. DOI: 10.1108/BFJ-08-2021-0872.

García-León, D., S. Contreras and J. Hunink, Comparison of meteorological and satellite-based drought indices as yield predictors of Spanish cereals. Agricultural Water Management, 2019. 213: p. 388-396. DOI: https://doi.org/10.1016/j.agwat.2018.10.030.

Jain, S.K., R. Keshri, A. Goswami, A. Sarkar and A. Chaudhry, Identification of drought-vulnerable areas using NOAA AVHRR data. International Journal of Remote Sensing, 2009. 30(10): p. 2653-2668. DOI: 10.1080/01431160802555788.

Jiao, W., L. Zhang, Q. Chang, D. Fu, Y. Cen and Q. Tong, Evaluating an Enhanced Vegetation Condition Index (VCI) Based on VIUPD for Drought Monitoring in the Continental United States. Remote Sensing, 2016. 8(3): p. 224.

Kogan, F.N., Global Drought Watch from Space. Bulletin of the American Meteorological Society, 1997. 78(4): p. 621-636. DOI: 10.1175/1520-0477(1997)078<0621:GDWFS>2.0.CO;2.

Kogan, F., L. Salazar and L. Roytman, Forecasting crop production using satellite-based vegetation health indices in Kansas, USA. International Journal of Remote Sensing, 2012. 33(9): p. 2798-2814. DOI: 10.1080/01431161.2011.621464.

Liu, W.T. and F.N. Kogan, Monitoring regional drought using the Vegetation Condition Index. International Journal of Remote Sensing, 1996. 17(14): p. 2761-2782. DOI: 10.1080/01431169608949106.

Maselli, F., S. Romanelli, L. Bottai and G. Maracchi, Processing of GAC NDVI data for yield forecasting in the Sahelian region. International Journal of Remote Sensing, 2000. 21(18): p. 3509-3523. DOI: 10.1080/014311600750037525.

Singh, R.P., S. Roy and F. Kogan, Vegetation and temperature condition indices from NOAA AVHRR data for drought monitoring over India. International Journal of Remote Sensing, 2003. 24(22): p. 4393-4402. DOI: 10.1080/0143116031000084323.

Smith, R.C.G., J. Adams, D.J. Stephens and P.T. Hick, Forecasting wheat yield in a Mediterranean-type environment from the NOAA satellite. Australian Journal of Agricultural Research, 1995. 46(1): p. 113-125.

Tucker, C.J., Red and photographic infrared linear combinations for monitoring vegetation. Remote Sensing of Environment, 1979. 8(2): p. 127-150. DOI: https://doi.org/10.1016/0034-4257(79)90013-0.

Unganai, L.S. and F.N. Kogan, Southern Africa's recent droughts from space. Advances in Space Research, 1998. 21(3): p. 507-511. DOI: https://doi.org/10.1016/S0273-1177(97)00888-0.

In your methods you mention that you spatially aggregated the standardised indices. Please elaborate on your practise applied with a focus on a) the spatial aggregation method of drought indices, were the standardised indices aggregated to province levels or the indicators (temp, precip.) and then the distribution done? And b) how did you aggregate the indices in time.

Thank you for bringing up the need for more details on how the aggregation was carried out in our study. We will make sure to include additional information on this aspect in the revised manuscript, with a specific focus on spatial aggregation. To address your questions:

a) Spatial aggregation:

To conduct the correlation analysis, we spatially averaged the meteorological variables (precipitation and PET) for each province and then calculated the standardised indicators based on the province-averaged time series. For vegetation indices, we first derived them at the pixel level for the entire country, and then used a land cover map to differentiate between forest and crop-covered pixels. We then calculated province-level vegetation indices averages separately for forest and crops, using the corresponding land cover mask.

Regarding the random forest modelling, we used the same data as for the correlation analysis, but grouped all the data belonging to the provinces included in each of the 6 regions. This was done because there was not enough data to train machine learning models at the provincial level.

b) Temporal aggregation:

We used monthly time series for most of our analyses, with the only exception being when we compared vegetation indices with crop yield data to validate the use of VIs as proxies for drought impact. In this case, we averaged the VIs over the growing season for each crop, as explained in lines 197-200 of the manuscript.

We hope that these additional details will address your concerns and provide a better understanding of the methods used in our study.

In my opinion, the discussion on your initial analysis (Fig 4) is a little short and could tolerate a little more discussion on possible drivers (maybe in the discussion section and not in the results). In figure 4b) East inland Thailand, there are three regions neighbouring, having the same major crops paddy rice (and high percentages), but there are either VHI, VCI or negatively correlated.--> why do they perform so different? Irrigation practise (e.g. river fed irrigation?) Elevation?

We agree that this is an interesting question that could be further investigated. However, we have deliberately kept that discussion short, as we conducted this analysis as a ~~quick~~ test to ensure that using vegetation indices as proxies for drought impacts was a reasonable assumption for the rest of our (main) analysis. Based on our results, we are generally satisfied with this assumption. However, there are some exceptions where neighbouring provinces with similar land cover, climatology and dominant crop show very different correlations with VIs, as you note in the case of some eastern provinces in Thailand. It is conceivable that differences in irrigation or agricultural practices, or in the outbreak of pests and diseases, could be contributing factors, but we do not have any evidence to support these hypotheses. Therefore, we have chosen not to delve further into this topic in the present study. However, we will highlight this gap in our revised manuscript and add a sentence as follows: '*In some cases, there is no obvious reason as to why the correlation is very different between two neighbouring provinces which share similar topography, land cover, climatology and dominant crop. Differences in irrigation or agricultural practices, or in the outbreak of pests and diseases, could be contributing factors. Exploring these factors in future research may provide insights into the observed differences in correlations.*'

Some minor points:

Figure 1-4 – Names of neighbouring countries are not readable

We thank you for bringing to our attention the issue with the readability of neighbouring countries' names in these maps. We will try to address this concern in the revised version. However, we would like to inform you that there are limitations to the modifications we can make to the background layer since we used ESRI Basemap, which has pre-set formatting and display for its layers. Nevertheless, we have made an effort to increase the font size of the country names by resizing the images. See for example the amended Figure 1:

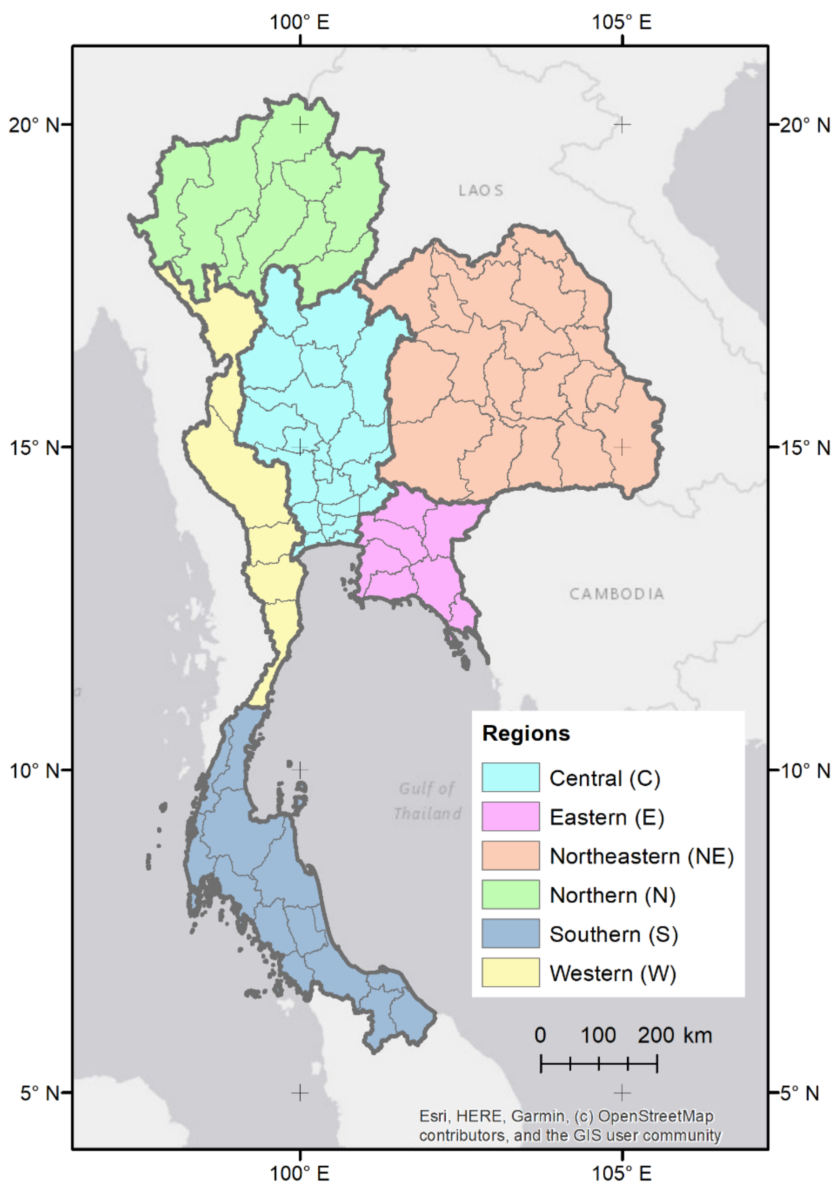
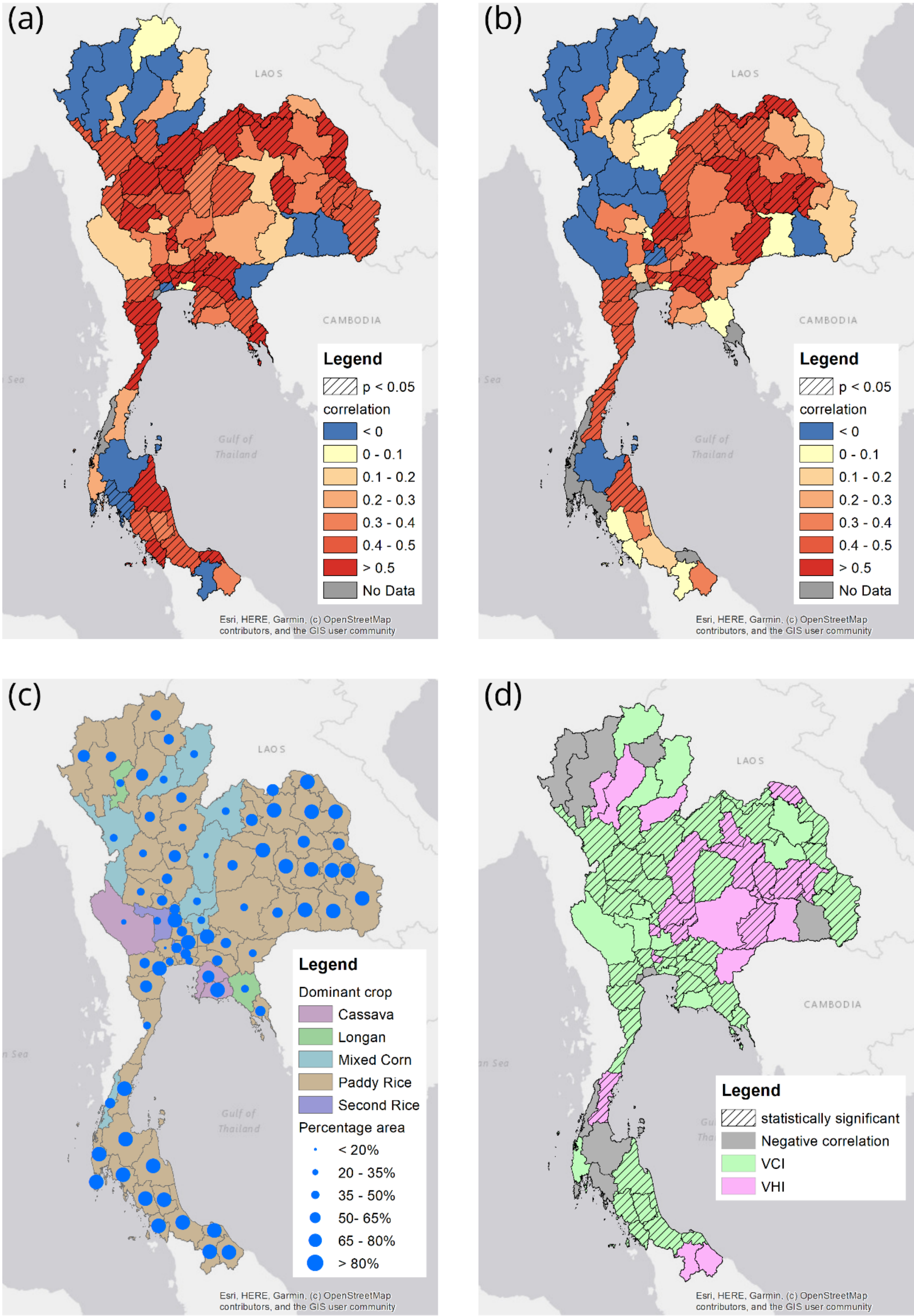


Figure 4+ please increase legend size

The legend for these maps will be made larger in the revised version.

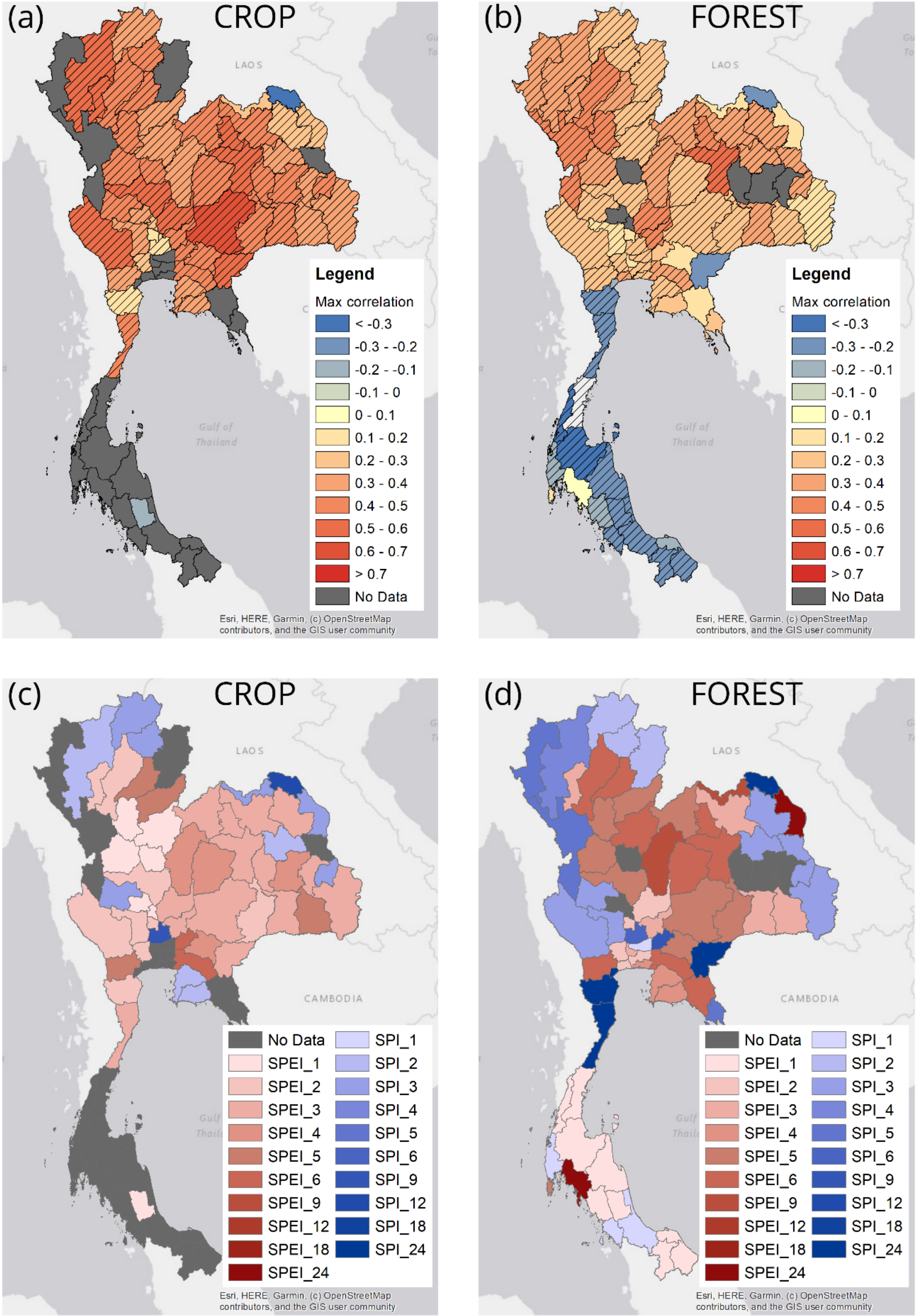
Please find the new Figures 4-6 in the following pages.

New Figure 4:

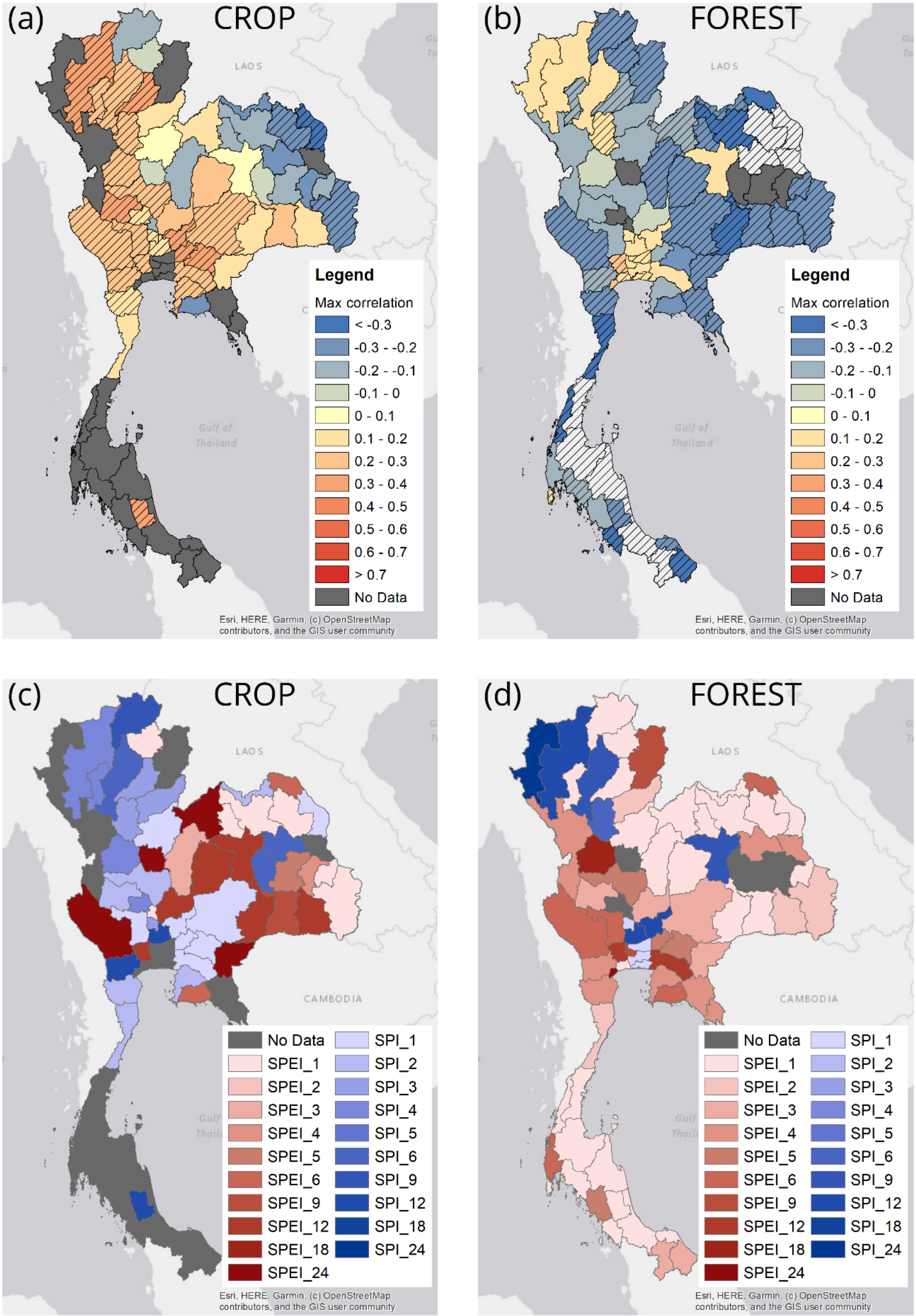


(a)
LAOS
CAMBODIA
Gulf of Thailand
Sea
Legend
p < 0.05
correlation
< 0
0 - 0.1
0.1 - 0.2
0.2 - 0.3
0.3 - 0.4
0.4 - 0.5
> 0.5
No Data
Esri, HERE, Garmin, (c) OpenStreetMap contributors, and the GIS user community
(b)
LAOS
CAMBODIA
Gulf of Thailand
Sea
Legend
p < 0.05
correlation
< 0
0 - 0.1
0.1 - 0.2
0.2 - 0.3
0.3 - 0.4
0.4 - 0.5
> 0.5
No Data
Esri, HERE, Garmin, (c) OpenStreetMap contributors, and the GIS user community
(c)
LAOS
Gulf of Thailand
Sea
Legend
Dominant crop
Cassava
Longan
Mixed Corn
Paddy Rice
Second Rice
Percentage area
< 20%
20 - 35%
35 - 50%
50- 65%
65 - 80%
> 80%
Esri, HERE, Garmin, (c) OpenStreetMap contributors, and the GIS user community
(d)
LAOS
CAMBODIA
Legend
statistically significant
Negative correlation
VCI
VHI
Esri, HERE, Garmin, (c) OpenStreetMap contributors, and the GIS user community

New Figure 5:


(a)
CROP
LAOS
Gulf of Thailand
Legend
Max correlation
< -0.3
-0.3 - -0.2
-0.2 - -0.1
-0.1 - 0
0 - 0.1
0.1 - 0.2
0.2 - 0.3
0.3 - 0.4
0.4 - 0.5
0.5 - 0.6
0.6 - 0.7
> 0.7
No Data
Esri, HERE, Garmin, (c) OpenStreetMap contributors, and the GIS user community
(b)
FOREST
LAOS
Gulf of Thailand
Legend
Max correlation
< -0.3
-0.3 - -0.2
-0.2 - -0.1
-0.1 - 0
0 - 0.1
0.1 - 0.2
0.2 - 0.3
0.3 - 0.4
0.4 - 0.5
0.5 - 0.6
0.6 - 0.7
> 0.7
No Data
Esri, HERE, Garmin, (c) OpenStreetMap contributors, and the GIS user community
(c)
CROP
LAOS
CAMBODIA
No Data
SPEI_1
SPEI_2
SPEI_3
SPEI_4
SPEI_5
SPEI_6
SPEI_9
SPEI_12
SPEI_18
SPEI_24
SPI_1
SPI_2
SPI_3
SPI_4
SPI_5
SPI_6
SPI_9
SPI_12
SPI_18
SPI_24
Esri, HERE, Garmin, (c) OpenStreetMap contributors, and the GIS user community
(d)
FOREST
LAOS
CAMBODIA
No Data
SPEI_1
SPEI_2
SPEI_3
SPEI_4
SPEI_5
SPEI_6
SPEI_9
SPEI_12
SPEI_18
SPEI_24
SPI_1
SPI_2
SPI_3
SPI_4
SPI_5
SPI_6
SPI_9
SPI_12
SPI_18
SPI_24
Esri, HERE, Garmin, (c) OpenStreetMap contributors, and the GIS user community

New Figure 6:



(a)
CROP
LAOS
Gulf of Thailand
Legend
Max correlation
< -0.3
-0.3 - -0.2
-0.2 - -0.1
-0.1 - 0
0 - 0.1
0.1 - 0.2
0.2 - 0.3
0.3 - 0.4
0.4 - 0.5
0.5 - 0.6
0.6 - 0.7
> 0.7
No Data
Esri, HERE, Garmin, (c) OpenStreetMap contributors, and the GIS user community
(b)
FOREST
LAOS
Gulf of Thailand
Legend
Max correlation
< -0.3
-0.3 - -0.2
-0.2 - -0.1
-0.1 - 0
0 - 0.1
0.1 - 0.2
0.2 - 0.3
0.3 - 0.4
0.4 - 0.5
0.5 - 0.6
0.6 - 0.7
> 0.7
No Data
Esri, HERE, Garmin, (c) OpenStreetMap contributors, and the GIS user community
(c)
CROP
LAOS
CAMBODIA
No Data
SPEI_1
SPEI_2
SPEI_3
SPEI_4
SPEI_5
SPEI_6
SPEI_9
SPEI_12
SPEI_18
SPEI_24
SPI_1
SPI_2
SPI_3
SPI_4
SPI_5
SPI_6
SPI_9
SPI_12
SPI_18
SPI_24
Esri, HERE, Garmin, (c) OpenStreetMap contributors, and the GIS user community
(d)
FOREST
LAOS
CAMBODIA
No Data
SPEI_1
SPEI_2
SPEI_3
SPEI_4
SPEI_5
SPEI_6
SPEI_9
SPEI_12
SPEI_18
SPEI_24
SPI_1
SPI_2
SPI_3
SPI_4
SPI_5
SPI_6
SPI_9
SPI_12
SPI_18
SPI_24
Esri, HERE, Garmin, (c) OpenStreetMap contributors, and the GIS user community

Furthermore, you might check on the following literature. Their results might be useful for some discussion and or introduction.

Sa-Nguansilp, C., Wijitkosum, S., Sriprachote, A., 2017. Agricultural drought risk assessment in Lam Ta Kong Watershed, Thailand. International Journal of Geoinformatics 13 (4), 37–43.

Monkolsawat, C., et al., 2001. An. Evaluation of Drought Risk Area in NE Thailand Asian Journal of Geoinformatics 1 (4), 33–44.

Wijitkosum S 2018. Fuzzy AHP for drought risk assessment in lam Ta Kong watershed, the north-eastern region of Thailand. Soil and Water Research, 13(4), 218–225. doi:10. 17221/158/2017-SWR

Thank you for bringing these references to our attention. We have reviewed them and believe they are relevant to our study, particularly in highlighting the vulnerability of the Northeast of Thailand to agricultural drought. We will cite these references in our introduction to provide additional context.