Authors response to Referee #2

RC2: Use of CHIRP dataset instead of the CHIRPS dataset. Please justify why the CHIRP dataset is used for the study area. Based on the study of Funk el al., 2015 it is proved that constraining the CHIRP by the CHPclim reduces systematic errors and the CHIRPS dataset produces low MAE and bias statistic than the CHIRP dataset.

AC: The authors are aware of the biases in the CHIRP dataset, but they aim at proposing an index for drought monitoring in near-real time; therefore, they selected the product with the shortest latency time. The main reason for using CHIRP instead of CHIRPS is the reduced latency time of the first dataset. In fact, as reported by (Funk et al., 2015), CHIRPS latency time is about three weeks; a preliminary version of CHIRPS with a 2-day latency time is available for GTS and Mexico only. In the case of CHIRP, latency time is about 2 days, and the product is available all over the world. CHIRP latency time can be checked at (Climate Hazard Group, 2015) by looking at the availability of the images.

Original manuscript: The use of CHIRP instead of CHIRPS (the Climate Hazard Group Infrared Precipitation with Stations) is related to the data latency time, which is shorter in the case of CHIRP since it doesn't include data from weather stations.

Author's changes to the manuscript (lines 107-111): The use of CHIRP instead of CHIRPS (the Climate Hazard Group Infrared Precipitation with Stations) is related to the data latency time. Since the aim of the work is the development of an index for near-real time drought monitoring, the product with the shortest latency time was selected. CHIRPS data have a latency time of about three weeks (Funk et al., 2015), while CHIRP's latency is about 2 days, as can be checked on the dataset website (Climate Hazard Group, 2015)

RC2: It would be interesting to see a comparison of the observed precipitation pattern with the used rainfall dataset. How close is the used dataset with the observed rainfall in Haiti? Please, provide scientific evidence in the revised manuscript which demonstrates the superiority of the used dataset when compared with the CHIRPS dataset for spatial and temporal (monthly) rainfall modelling at the study area.

AC: Unfortunately, as highlighted by (Mari et al., 2015) "Systematic collection of rainfall through rain gauges has been relatively rare in post-earthquake Haiti, with on-the-ground rainfall measurements available only for Ouest (by USGS) and Sud (by Haiti Regeneration Initiative) departments". A map of existing rain gauges in Haiti reported in Eisenberg et al. (2013) shows the presence of only 5 gauges all over the country recording for a short period of time. Thus, a comparison between observed precipitation and rainfall retrieved from satellite images is not very feasible. The authors tried to overcome the issue providing a comparison with observed drought events, retrieved from text-based documents and international disasters databases, in Section 3.4 of the manuscript.

RC2: Vegetation Health Index: It should be mentioned that all remote sensing indices could be expressed as deviations from the mean using the standardization procedure (i.e. Mckee at al., 1993) as used by Peters et al. [2002]. Hence the adopted classification of VHI using Eq. 1 is a transformation procedure of the typical VHI (from 0 to 1) to a normal distribution using the standardization procedure as proposed by Peters et al.,[2002]. I recommend to the authors to clarify this issue on the revised manuscript and to mention that equal weighting is used for VCI and TCI.

AC: All these comments will be addressed in the revised manuscript as follows.

Original manuscript: The VHI is a remote-sensing index developed to include the effects of temperature on vegetation; in fact, it combines the VCI with the Temperature Condition Index (TCI), which is another remote-sensing index used to determine vegetation stress caused by temperature and excessive wetness. One drawback of the VHI is the impossibility to identify the cause of the vegetation stress; in fact, vegetation can suffer because of various events: excessive wetness, pests, fires, droughts or others. It is a biophysical

indicator of a lack of precipitation but can also be seen as representing drought impacts on the ground (Bachmair et al., 2016). It goes from 0, which stands for vegetation in very bad conditions to 100, meaning perfectly healthy vegetation. The classification scheme of VHI, as proposed in (Dalezios et al., 2017) is presented in Table 4.

The VHI is standardized according to the following equation:

$$VHI_{st} = \frac{VHI - \overline{VHI}}{\sigma}$$

where $\overline{VHI}$ is the mean of the distribution and σ its standard deviation. The standardized variable, VHI_{st}, has a distribution with 0 mean and 1 as standard deviation.

Author's changes to the manuscript (lines 134-144): The VHI is a remote-sensing index developed to include the effects of temperature on vegetation; in fact, it combines the VCI with the Temperature Condition Index (TCI) which is another remote-sensing index used to determine vegetation stress caused by temperature and excessive wetness. The VHI is based on a linear combination of VCI and TCI, $VHI = \alpha VCI + (1 - \alpha)TCI$. As suggested by Kogan et al. (2016), when VCI and TCI contributions are not known $\alpha = 0.5$. One drawback of the VHI is the impossibility to identify the cause of the vegetation stress; in fact, vegetation can suffer because of various events: excessive wetness, pests, fires, droughts or others. It is a biophysical indicator of a lack of precipitation but can also be seen as representing drought impacts on the ground (Bachmair et al., 2016). It goes from 0, which stands for vegetation in very bad conditions to 100, meaning perfectly healthy vegetation. The classification scheme of VHI, as proposed in Dalezios et al. (2017), is presented in Table 4.

The VHI is standardized to make comparisons with the SPI easier. As mentioned by Peters et al. (2002), all remote-sensing indices can be expressed as deviations from the mean; therefore, the standardized variable, VHI_{st}, is computed according to the following equation:

$$VHI_{st} = \frac{VHI - \overline{VHI}}{\sigma}$$

Thus, the same procedure proposed in Peters et al. (2002) in the case of the NDVI has been applied to the VHI.

RC2: Furthermore, please discuss why VHI is used using the approach of Kogan and why VHI and TCI are not first standardized and then combined with equal [see also Bento et al., 2018a,b] weighting in a probabilistic form to give the VHI (similar approach to PPVI or the approach of multivariate distributions using parametric [Hao and AgaKouchack, 2013] or a non-parametric approaches [Hao and AgaKouchack, 2014]

AC: The VHI as proposed by Kogan was used since it is a consolidated product, already applied to monitor vegetation health in various studies concerning different topics such as food security (Kogan, 2019), insurance (Bokusheva et al., 2016) and drought identification (Pei et al., 2018; Sholihah et al., 2016). As above mentioned, the VHI was standardized to facilitate the interpretation of the index inside the bivariate context. PPVI values do not change if PPVI is computed by combining SPI3 and non-standardized VHI through the bivariate normal distribution function (see panel (a) of Fig. 1). In addition, the authors computed VHI_{st} by a linear combination of standardized TCI (TCI_{st}) and standardized VCI (VCI_{st}), applying equal weighting of the two indices, with TCI_{st} and VCI_{st} computed according to Peters et al. (2002). PPVI values do not change, as shown in panel (b) of Figure 1.

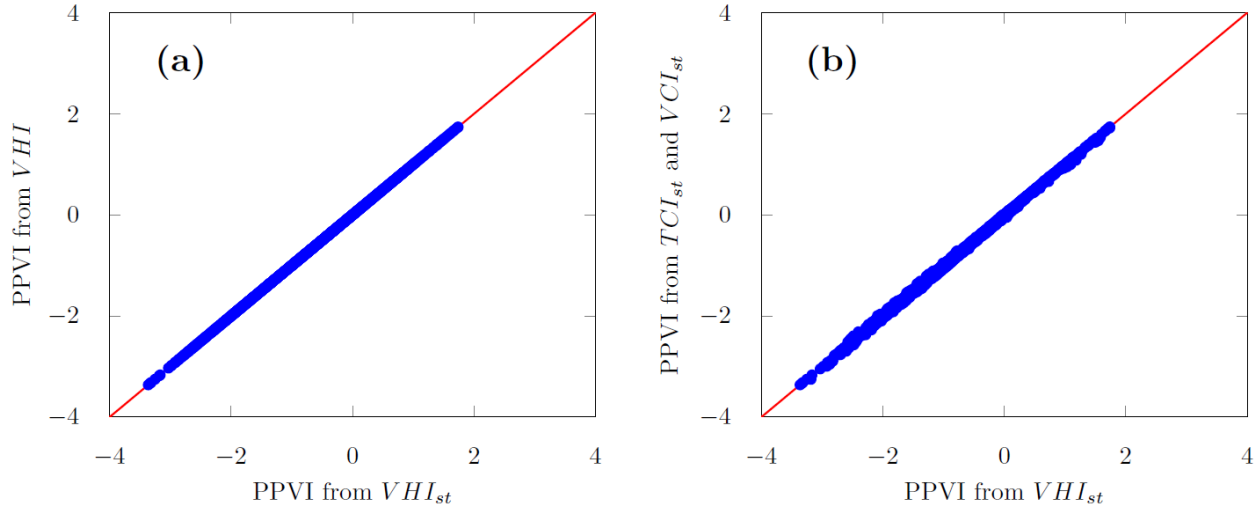

Figure 1: (a): relationship between PPVI computed from VHI_{st} and PPVI computed from VHI; (b): relationship between PPVI computed from VHI_{st} and PPVI computed from VHI_{st} retrieved from linear combination of VCI_{st} and TCI_{st}.

RC2: Comparison with identified drought events. Is it possible to include a section with a comparison of PPVI with historical identified drought events? This comparison could exemplify the proposed index and strengthen the scientific quality of the manuscript.

AC: The comparison with identified drought events, reported in Table 7 of the original manuscript and identified from text-based documents such as governmental reports and international disaster databases, is already reported in the manuscript in Section 3.4, "Indices comparison", where PPVI performance in reproducing observed drought events is compared with SPI3 and VHI performance. To make the manuscript clearer on this aspect, Section 3.4 "Indices comparison" will be renamed in "Comparison of drought indices with observed drought events". In addition, Figure 2 will be added in Section 3.4 (as Figure 7 in the revised manuscript) to allow an easy comparison between drought indices performance in identifying observed drought events.

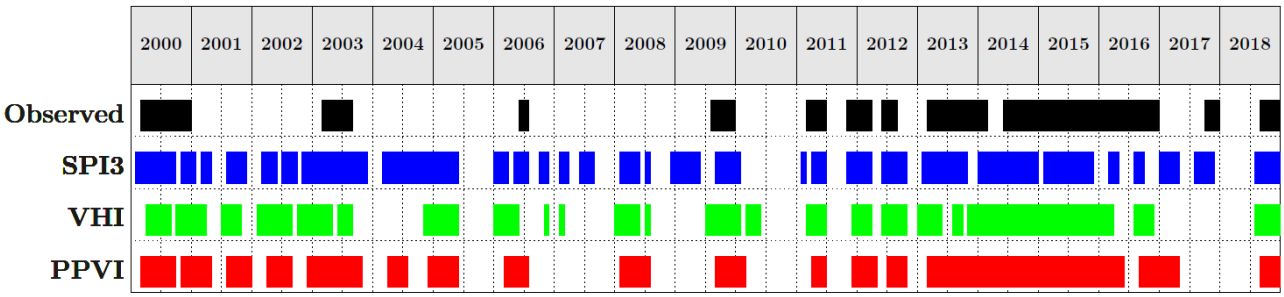

Figure 2: comparison between observed drought events and drought events identified by PPVI, SPI3 and VHI when calibrated with the best performing parameters shown in Table 10. The comparison is shown for the period from 2000 to 2018.

Table 10 will be modified to show the best performing parameters not only for PPVI but for all the three indices.

Table 10: Best configuration parameters for the model when applied with PPVI, SPI3 and VHI.

	Z	z	N	n	TN	FP	FN	TP	POFD	POD
PPVI	-1.8	-1.1	30%	8%	957	379	99	506	0.284	0.836
SPI3	-1.3	0	20%	8%	943	393	157	448	0.294	0.740
VHI	22	40	10%	8%	935	401	150	455	0.300	0.752

References:

Bachmair, S., Stahl, K., Collins, K., Hannaford, J., Acreman, M., Svoboda, M., Knutson, C., Smith, K. H., Wall, N., Fuchs, B., Crossman, N. D., & Overton, I. C. (2016). Drought indicators revisited: the need for a wider consideration of environment and society. *Wiley Interdisciplinary Reviews: Water*, *3*(4), 516–536. https://doi.org/10.1002/wat2.1154

Bokusheva, R., Kogan, F., Vitkovskaya, I., Conradt, S., & Batyrbayeva, M. (2016). Agricultural and Forest Meteorology Satellite-based vegetation health indices as a criteria for insuring against drought-related yield losses. *Agricultural and Forest Meteorology*, *220*, 200–206. https://doi.org/10.1016/j.agrformet.2015.12.066

Climate Hazard Group. (2015). *Chirp daily*. ftp://ftp.chg.ucsb.edu/pub/org/chg/products/CHIRP/daily/

Dalezios, N. R., Tarquis, A. M., & Eslamian, S. (2017). Droughts. In N. Dalezios (Ed.), *Environmental Hazards Methodologies for Risk Assessment and Management*. IWA Publishing. https://doi.org/https://doi.org/https://doi.org/10.2166/9781780407135,

Eisenberg, M. C., Kujbida, G., Tuite, A. R., Fisman, D. N., & Tien, J. H. (2013). Examining rainfall and cholera dynamics in Haiti using statistical and dynamic modeling approaches. *Epidemics*, *5*(4), 197–207. https://doi.org/10.1016/j.epidem.2013.09.004

Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A., & Michaelsen, J. (2015). The climate hazards infrared precipitation with stations - A new environmental record for monitoring extremes. *Scientific Data*, *2*, 1–21. https://doi.org/10.1038/sdata.2015.66

Kogan, F., Guo, W., Strashnaia, A., Kleshenko, A., & Chub, O. (2016). *Modelling and prediction of crop losses from NOAA polar-orbiting operational satellites*. *5705*. https://doi.org/10.1080/19475705.2015.1009178

Kogan, F. N. (2019). Application of Vegetation Health Data and Products for Monitoring Food Security. In *Remote Sensing for Food Security* (pp. 225–241). Springer, Cham. https://doi.org/https://doi.org/10.1007/978-3-319-96256-6_10

Mari, L., Bertuzzo, E., Finger, F., Casagrandi, R., Gatto, M., & Rinaldo, A. (2015). On the predictive ability of mechanistic models for the Haitian cholera epidemic. *Journal of Royal Society Interface*, *12*.

Pei, F., Changjiang, W., Xiaoping, L., Xi, L., Kuiqi, Y., Yi, Z., Kun, W., Li, X., & Gengrui, X. (2018). Monitoring the vegetation activity in China using vegetation health indices. *Agricultural and Forest Meteorology*, *248*, 215–227.

Peters, Al. J., Walter-Shea, E. A., Ji, L., Vina, A., Hayes, M., & Svoboda, M. D. (2002). Drought monitoring with NDVI-based Standardized Vegetation Index. *Photogrammetric Engineering & Remote Sensing*, *68*(1), 71–75.

Sholihah, R. I., Trisasongko, B. H., Shiddiq, D., Ode, L., & Iman, S. (2016). Identification of agricultural drought extent based on vegetation health indices of Landsat data : case of Subang and Karawang , Indonesia. *Procedia Environmental Sciences*, *33*, 14–20. https://doi.org/10.1016/j.proenv.2016.03.051