Interactive comment on "Remote sensing in an index-based insurance design for hedging economic impacts on rice cultivation" by Omar Roberto Valverde-Arias et al.

Anonymous Referee #1

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The paper presents the definition of an index-based insurance for possible losses on rice production due to weather extreme events using remote sensing and field data.

The paper well fits with the journal and the special issue and is recommended for publication after some possible improvements. Despite the number of comments, these are not related to substantial changes, but in some cases alternative approaches should be considered and some results should be better presented.

We appreciate and thank reviewer's comments and we revised the manuscript according to them.

<u>Comments on data, methods and results.</u>

1) Have you considered the option of using EVI instead of the NDVI? In some cases, it can show better estimates of yield than NDVI. It could be useful to motivate the choice.

Thank you for the comment and suggestion. We have tested different vegetation indexes at the beginning of this research (NDMI, NDFI, SAVI and EVI); being NDVI and EVI the ones with the best performance both detecting drought and flood impacts and estimating yield. Between NDVI and EVI, we did not find significant differences. Thus, we finally chose NDVI because this index is the most used and documented in similar studies. We think that EVI could have some advantages if we would use not highly-processed imagery where atmospheric correction could make the difference.

See in the manuscript lines 80-84

Particularly, the Normalized Difference Vegetation Index (NDVI) or the Enhanced Vegetation Index (EVI) are the ones performing the best in terms of detection of drought and flood impacts and estimating yields, being NDVI one of the most used in crop monitoring and current IBI systems as mentioned in many literature, e.g. (Rhee et al., 2010; Van Tricht et al., 2018; Vroege et al., 2019; Zhang et al., 2017)

2) Have you used quality information to filter MODIS data considered in the analysis? Being the rainy season there can be a high influence of clouds, but it seems that quality information have not been considered. This can be explained and motivated.

Yes, we considered information on data quality and explained it in the revised version of the paper (see lines 145-148). The MODIS imagery is a highly processed product in order to use the best available pixel in the composite image. Additionally, we used the Quality Assurance layer (quality layer: 250m 16 days VI Quality) included in the HDF file of NDVI MODIS imagery. In this layer, each pixel has a rank key that identifies the pixel quality, the rank key = 0 means good data, use it with confidence. Then, we used only pixels with 0 rank key following MODIS Vegetation Index User's Guide (Didan et al., 2015).

3) Have you considered the possibility of using other statistics of NDVI (max, percentiles?). It can be interesting to see if the average was the best one.

The majority of insurance cases use historical data for set a curve of NDVI mean along the year and they consider between one or two standard deviations under the mean for identifying the occurrence of an extreme event impact, as the case of Spain. They have determined that the NDVI average is an adequate crop state estimator (Dario, 2015; Vrieling et al., 2014; Vroege et al., 2019). Our approach is similar but instead of monitoring the NDVI along each stage of rice crop cycle during rainy season, we used the NDVI average of the entire rice crop cycle. If the impact of an extreme event occurs in a particular stage of rice-crop cycle, it is going to be reflected in the NDVI_ave.

4) You define extreme events based only on precipitation, but this rather a big simplification. The description of what you consider extreme event should be more evident and I would suggest explain why you adopted this simplified approach. Further, since the two considered zones have rather different precipitation regimes, should extreme precipitation-related event have different thresholds?

Actually, we defined extreme events through their impact over rice crop, which is evidenced in NDVI of rice cultivation. The climatic data is not enough robust yet in Ecuador, for using a climatic index as precipitation, temperature, evapotranspiration or hydric balance. Thus, we used a vegetation index. We have analysed the NDVI time series imagery of rice crop cycle during seventeen rainy seasons; in order to identify anomalous years. The years had been classified in five categories, according to their NDVI mean and median (LSD and Bonferroni analysis); the two lowest categories would correspond to extreme-climatic impacted years, respect to regular years. We already knew that the years from the two lowest categories were impacted by droughts and floods, because they are the only events capable to have a regional extend which impact can be detected through satellite imagery. Moreover, these years have been widely documented, because these phenomena (drought and flood) are mostly caused by El Niño Southern Oscillation (ENSO), that not only affects agriculture but infrastructure and people in general. Thus, in order to have a confidence source of climatic data, we used the NOAA climatic application, through which we have found that the years from the lowest categories also present precipitation anomalies (drought and flood). In this way, we established the relationship between the impact over rice crop (evidenced in low NDVI) and the cause of that impact, the extreme events (drought and flood).

With respect to the use of different thresholds for each zone, our thresholds are not climatic but physiologic and economic. The physiologic threshold cannot be differentiated; because it represents a crop damage threshold, the damage level is independent of the zone. It depends on the intensity of the extreme event. Thus, for reaching the same damage level in both zones, we need to have an event with the same intensity. However, the probability to have an event with a determined magnitude in each zone is different, as it is shown in the risk status analysis. We used these probabilities in our calculations. For this reason, it is not necessary to set a different physiologic threshold in each zone. On the other hand, the economic threshold was differentiated according to the conditions of each zone.

5) Looking at Figure 3A, is seems that even a linear fitting could give a good result: have you tried it? How large is the difference with the normal accumulative curve?

Yes, we tried the linear regression and it fits well, but it has a problem with NDVI values over 0.8 and bellow 0.2. It is because, NDVI is saturated and it does not respond linearly over 0.8 values, on the contrary, NDVI below 0.2 does not correspond to crop coverage. Being the normal accumulative curve the one that fits better for yield estimation.

6) Looking at figure 3B is possible to see several cases of large under/over production estimates: have you checked those cases?

Yes, we noticed that. It could be because we did not have control on the yield-sampling methodology. We had to use geo-referenced yield data from another project that fit with our study area spatially and temporary. We believe that, if we could have access to data more adequate to our working scale, we would get better results. However, despite this, the statistical analysis shows us that the majority of the sampled NDVI and yield correlated properly.

It is explained in lines 187-193

The General Coordination of the National Information System (CGSIN-acronym in Spanish-) of Ecuadorian Agricultural and Livestock Ministry (MAG) has conducted a rice-yield estimation project since 2014 when it began sampling yields across mapped rice areas (Moreno, 2014). Thus, 369 georeferenced rice-yield observations (t/ha) were available for 2014-2017 rainfed cycles (January to May) in the study area over AHZs *f7* and *f15* (see, Fig. 1 C). Therefore, we used these rice yield observations with their corresponding spatial and temporal NDVI_ave values for obtaining the parameters included in Eq. (2) (Valverde-Arias et al., 2019). The robustness of this model was evaluated through the RMSE (%) and R-squared coefficient.

Specific comments on figures.

Figure 1: this figure can be merged with Figure 2 saving space (maybe Latin America map can be removed) and figure 1A is similar to figure 2 but not dividing coloured area in zones. Figure 2: see above Figure 3: the graph in figure A seems that could be fitted also linearly: how different would it be? Figure 4: images should all use the same legend, otherwise the comparison lead to wrong interpretation. Further, reducing the area to a smaller region can simplify making legend uniform. Figure 5: axis should be the same in all graphs. Figure 6: axis should be the same in all graphs.

Agree; a new combined figure has been included (Fig. 1).

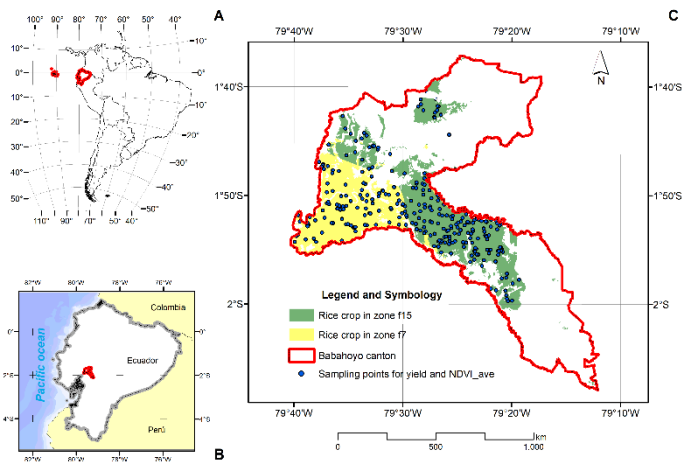

Figure 1. A) Location of Ecuador in South America, B) location of Babahoyo canton in Ecuador, and C) Agro-ecological homogeneous zones *f7* and *f15* over rice cultivation area with yield observations in Babahoyo canton

With respect to figure 3, please see answer to reviewer's comment 5 above.

With respect to figures 4, 5 and 6, we agree with the reviewer and all figures have been changed in revised manuscript (now figures 3, 4 and 5) according to the provided comments.

Specific comments on tables.

Table 1: this table do not provide many additional information and can be removed, if you want.

Agree. The table 1 was removed

Table 6: The use of the symbol > is a bit misleading, so I'd remove it and the unit of precipitation maybe is missing the time period.

We corrected table 6; in the new version is table 5. The mistaken symbol > from the altitude data was removed and we added the time period in precipitation data units.

Table 7: it seems there is some inconsistency between table and text, since Z is negative in Scenario 2 and not in Scenario 1. Further, many information are repeated in the table: would it possible to remove repetition and improve the readability?

We misplaced the scenarios in table 7, it was corrected, table 6 in new manuscript

Table 8: the first column is a class, but it show just a single value. Maybe it would be better to show the boundary values of each class. The table could be also replaced by a graph.

We add the range and we change the table 8 by the figure 6

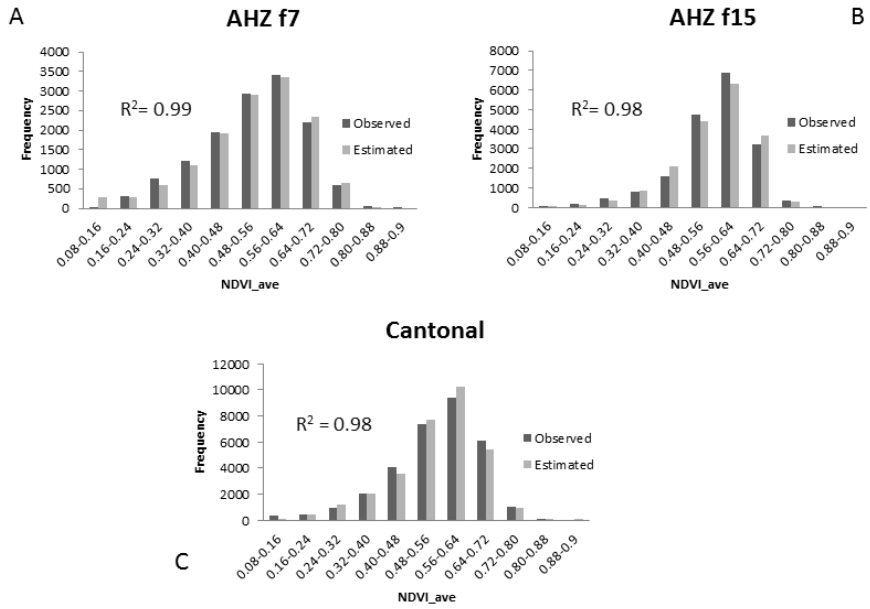

Figure 6. Frequency distribution of NDVI_ave values both observed in imagery data and estimated through GEVmim distribution in: A) *f7*, B) *f15* and C) cantonal

Tables 9 and 10: would it be possible to merge these tables? Further why the price should be always either 371 or 371.5.

We used the official price of rice in the last three years, the price is very variable among months and years, but, if we observe it in a particular time, it is going to be the same in both zones. It means that it is not a differencing variable between these two zones.

The tables 9 and 10 were merged in the new table 7

Table 7. Indemnity calculation for physiologic and economic thresholds, for each AHZ (*f7* and *f15*) and cantonal, both in scenario 1 and 2

	Expected Yield* (t/ha)	Price (USD/t)	Gross incomes (USD/ha)	Production cost scenario 1 (USD/ha)**	Gross margin scenario 1 (USD/ha)	Production cost scenario 2 (USD/ha) ***	Gross margin scenario 2 (USD/ha)
				Physiologic threshold			
Cantonal	2.65	371.50	984.4	1259	**-274.62**	1259	**-274.62**
f7	2.65	371.50	984.4	1022	**-37.62**	1259	**-274.62**
f15	2.65	371.50	984.4	1629	**-644.62**	1259	**-274.62**
				Economic threshold			
Cantonal	5.65	371.50	2099	1259	**840.21**	1259	**840.21**
f7	5.11	371.50	1899	1022	**877.28**	1259	**640.28**
f15	6.68	371.50	2482	1629	**853.31**	1259	**1223.32**

Table 11: it might be useful to add a column with the compensation per ha, before the total compensation for a 20 ha farm.

Agree. The suggested column was added (see the new table 8)

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