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.

Comments on data, methods and results.

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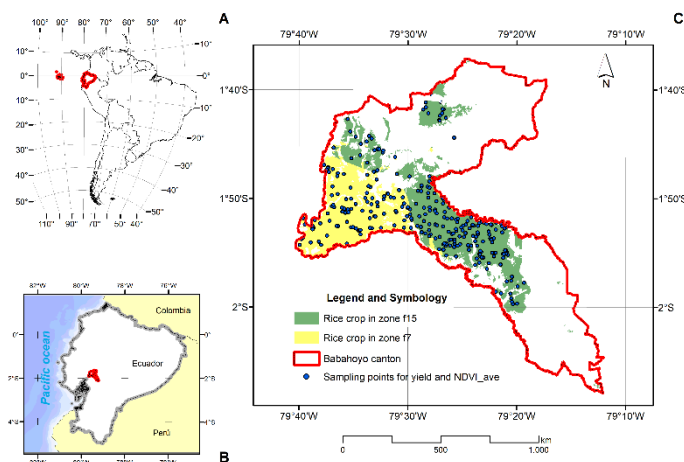
Figure 1. A) Location of Ecuador in South America, B) location of Babahoyo canton in Ecuador, and C) Agro-ecological homogeneous zones *f7* and *f15* over rice cultivation area with yield observations in Babahoyo canton

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 (**In revised manuscript 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 former 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 new **figure 6**
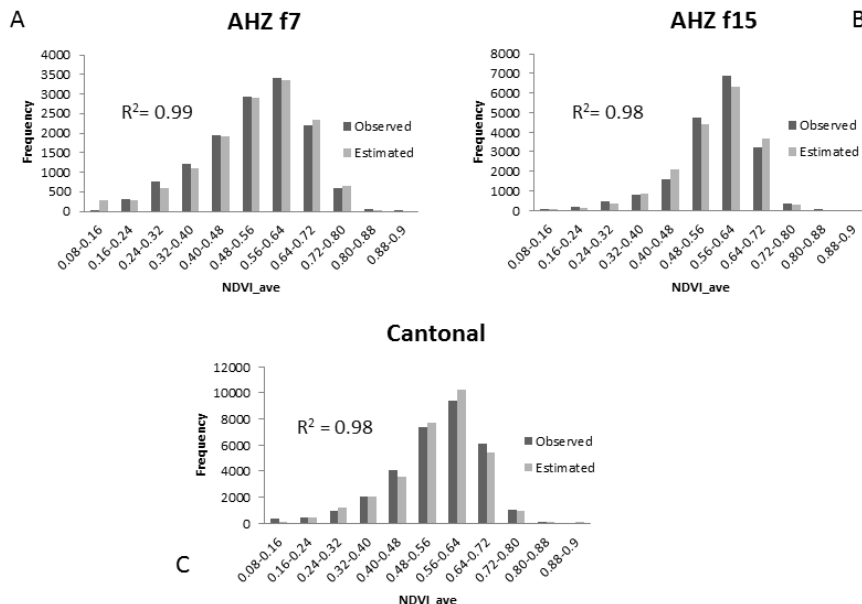
Figure 6. Frequency distribution of NDVI_ave values both observed in imagery data and estimated through GEVmim distribution in: A) *f7*, B) *f15* and C) cantonal

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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Anonymous Referee #2

General comments: The paper is within the scope of the journal. The paper is characterized by scientific innovation and generality, since the methodology can be applied in different regions and climatic environments. In that sense, it is extremely useful presentation of a new approach. The paper is very well and analytically presented with detailed description of the steps followed and explanation of the corresponding results.

Thank you very much for your positive comments, questions and suggestions for improvement. Below we answer to them and explain the changes made to the manuscript.

Technical-scientific comments:

1) Lines 79 and 118. In reviewing the existing remote sensing literature, it is worth to mention the system Copernicus, with Sentinel 1, or 2 or 3, which is very promising with improved

resolution (20-30 m) and what is the expected improvement in the accuracy of the analysis. The authors should add comments and and/or comparisons.

We agree with the comment. We have included some examples of using Sentinel imagery in crop monitoring; and for sure, it will be an important source of data in future applications of IBI. But so far, there are not enough historical data available of Sentinel (since 2014) for being used in an IBI design. However, once we have designed the IBI application, it can be used for monitoring the crop state due to its high temporal and spatial resolution (10 days and 10-60m respectively).

The improvement of Sentinel imagery in temporal and spatial resolution with respect to MODIS imagery, could allow us to discriminate much better the extreme climatic events' impact over crops. Additionally, it could be used for IBI design for other crops that are cultivated in small and scattered parcels, as maize in Ecuador.

We explained this in **lines 129-139**:

Satellite imagery data were obtained from the MODIS MOD13Q1V6 product (NASA LP DAAC, 2015) (See Didan et al. (2015) for a description of its characteristics). MODIS imagery was selected due to its long temporal coverage (imagery data available since 2001), which is necessary for constructing a historical sequence of NDVI. MODIS's spatial resolution 250 m is moderate, but for regional applications of crop monitoring this resolution is sufficient (Jiao et al., 2019; Sánchez et al., 2018). Since 2015, Sentinel 2 imagery is available with a resolution of 10 to 60 m depending on the bands. Many studies have used Sentinel for monitoring crops state with very positive results (Inglada et al., 2015; Van Tricht et al., 2018; Veloso et al., 2017). However, current time data series availability of Sentinel does not allow its use for IBI design, as at least 10 years of historical data are needed for an insurance design (Rao, 2010). Despite this, Sentinel will become in the coming years an important alternative in the insurance field. Also, Sentinel 1, which is a radar sensor, could be an interesting option for rice monitoring in those zones where steadily presence of clouds represent a problem, as Torbick et al., (2017) mentioned in their study

2) Lines 73, 83-84 and 113. Agroecological zones. The proposed methodology uses principal component analysis (PCA) for classification. The subject of agro climatic classification and zoning is large, which considers different methodologies, including combinations of satellite indices, besides PCA. The authors should mention the main existing literature in the subject, since there might be potential improvement of the conducted agroecological zoning.

Thank you for the comment that we fully support. However, the agro-ecological zoning was the main subject in our first article (Arias et al., 2018), where our methodology was compared with other zoning methodologies. Further, this zoning was evaluated through satellite imagery for validating our resulting AHZs in a second article (Valverde-Arias et al., 2019). We did not explain this in the paper in order to focus on the IBI design. However, now we have clarified this in **lines 123-124**:

This zoning was evaluated through NDVI imagery in the study of Valverde-Arias et al., (2019), which proved that this zoning is adequate and necessary for designing an efficient IBI, reducing basis risk

3) Line 127. A clarification is required about the NDVI_ave data used: (1) these are annual values?, (2) which means that for each pixel there are 17 values? (3) How the sample points

of 30% are selected? randomely? Why only 30%? (4) the rest are used for validation or not used at all?

NDVI_ave is the average of all NDVI measures of rice crop cycle (January to May) for each observation point, i.e. the average of the 10 NDVI measures obtained every 16 days from January to May (5 months, 2 measures per month). This means that we have one average value per year (i.e. 17 values, from 2001 to 2017) that corresponds to an average of NDVI measures along 5 months. See **lines 140-143 and 150-151**.

With respect to the sample size, we followed the equation below (Olofsson et al., 2014), which is used for calculating the adequate sample size in a stratified random sampling of geographic products. As result of this evaluation, we obtained that the adequate stratified sample size is 12,77% of the total pixels in each AHZ. We wanted to make sure not to use a lower sample size than 12%. Thus, just for researching purposes, we decided to use 30% to ensure the representativeness of the sample. However, in our former paper in which we assessed the optimum sample size in a practical Index based insurance application, we found that even the 10% is significant representative, because the homogeneity within AHZs is very high.

The sample points were generated by an ArcGis tool that produces random sample points homogeneously distributed in the different strata (AHZs f7 and f15) in the study area. We didn't use a higher sample size or the total pixels because statistically it is not necessary, and it would increase our data processing and storage requirements. If we consider that we processed data of 17 years that increment could overcome our analysis capacity.

$$n = \frac{(\sum W_i S_i)^2}{[S(\hat{O})]^2 + (\frac{1}{N})\sum W_i S_i^2} \approx \left(\frac{\sum W_i S_i}{S(\hat{O})}\right)^2$$

Where,
N is number of units in the area of interest (number of overall spatial units (pixels)
$S(O)$ is the standard error of the overall accuracy that we would like to achieve
Wi is the mapped proportion of area of class *i*, and
Si is the standard deviation of stratum *i*

We clarified this in **lines 152-163**

4) Line 142. For rice estimation, what NDVI_ave values are used? annual per pixel?III.

We used the pixels' NDVI average during rice-crop cycle of rainy season (Jan-May) that corresponds temporary (same year) and spatially with the geo-referenced point of the rice-yield data. This means there is one value of NDVI_ave per year and pixel.

Technical corrections:
1. Line 102. Never a sentence starts with number...: insteadof 84%, write: " , where 84%...".
     It was corrected in **line 107**

2. Line 120. Instead "... the precipitations", write"rainy season".
     It was corrected in **line 143**

3. Line 277. Instead of "Once that...", write "Since..."

4. Line 304.Never a sentence starts with number...: instead of 25%, write: " , where 25%..."

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List of the relevant changes made in the revised manuscript

It was included a new paragraph in **lines 80-84 about the reason for selecting NDVI in our study among others vegetation indexes.**

We added **lines 123-124** in the paragraph of Agro-ecological Homogeneous zones to clarify our zoning methodology and for indicating that further information can be found in (Arias et al., 2018)

It was included the new paragraph in **lines 129-139,** about the process of pixel selection taking account the pixel quality indicator of MODIS imagery. Additionally, a paragraph in which we mentioned the possible alternative to use Sentinel imagery in future Index based insurance applications.

We include the paragraph **in lines 152-163** for clarifying the sample size calculation.

It were merged the former Fig. 1 and 2 in a new Fig. 1 **(in the revised manuscript).**

In the former Figure 4, they were corrected the scale legend bar of included maps **(in revised manuscript Fig. 3).**

In Figures 5 and 6, we standardized the maximum Y axe's value, setting all of them in five (**In revised manuscript figures 4 and 5)**.

The former Table 1 was removed in the new manuscript

We corrected Table 6; in the new version is T**able 5**. The mistaken symbol > from the altitude data was removed and we added the time period in precipitation data units (mm/year).

We misplaced the scenario 1 and 2 in former Table 7. It was corrected in **Table 6** in new manuscript.

We eliminated the Table 8 and replaced it by the new F**igure 6**

The Tables 9 and 10 were merged in the new **Table 7**

We included a new column with the compensation value per hectare, in the former Table 11, now it is the **Table 8 in the new manuscript.**

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Remote sensing in an index-based insurance design for hedging economic impacts on rice cultivation

Omar Roberto Valverde-Arias[1], Paloma Esteve[12], Ana María Tarquis[13], and Alberto Garrido[12]

[1]CEIGRAM, ETSIAAB, Universidad Politécnica de Madrid, Madrid, 28040, Spain

[2]Dpto. de Economía Agraria, Estadística y Gestión de Empresas, ETSIAAB, Universidad Politécnica de Madrid, 28040 Madrid, Spain

[3]Grupo de Sistemas Complejos, ETSIAAB, Universidad Politécnica de Madrid, 28040 Madrid, Spain

Correspond to: Omar Valverde (omar.valverde@upm.es)

Abstract:

Rice production in Ecuador is steadily affected by extreme climatic events that make it difficult for farmers to cope with production risk, threatening rural livelihoods and food security in the country. Developing agricultural insurance is a policy option that has gained traction in the last decade. Index-based agricultural insurance has become a promising alternative that allows insurance companies to ascertain and quantify losses without verifying a catastrophic event in situ, lowering operative costs and easing implementation. But its development can be hindered by basis risk, which occurs when real losses in farms do not fit accurately with the selected index. Avoiding basis risk requires assessing the variability within the insurance application area and considering it for representative index selection. In this context, we have designed an index-based insurance that uses a vegetation index (NDVI) as indicator of drought and flood impact on rice in Babahoyo canton (Ecuador). Babahoyo was divided in two Agro-ecological Homogeneous Zones to account for variability, and two NDVI threshold values were defined to consider, first, the event impact on crop (physiologic threshold), and, second, its impact on gross margin (economic threshold). This design allows us to set-up accurate insurance premiums and compensations that fit the particular conditions of each AHZ, reducing basis risk.

1   Introduction

Rice cropping area in Ecuador is witnessing a reduction trend along recent years (FAO, 2018). From an average cultivated area around 400,000 ha between 2005 and 2015, annual average decreased to 385,039 ha in 2016 and to 370,406 ha in 2017, falling considerably to 301,853 ha in 2018 (Aguilar et al., 2015, 2018; INEC, 2018; Montaño, 2005). Such a downward trend rises Government's concern as rice production plays an important role in Ecuadorian food security (Pinstrup-Andersen, 2009) and it is central to rural livelihoods in certain areas of the country. Daily rice consumption per person is 115g (Montaño, 2005), which represent currently an annual demand of 714,000 tonnes. Additionally, rice production in Ecuador offers employment to 22% of the economically active population, involving around 140,000 families. For these reasons, Ecuadorian government supports rice producers through technical advice, subsidized inputs, credit lines for farm modernisation, and minimum support prices (Eymond and Santos, 2013). However, these supporting mechanisms have not prevented efficiently the gradual reduction of rice cropping area, being necessary to adopt additional measures that support stability of farmers' revenues.

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FAO and UN-Habitat, (2010) reported the 29 most important disasters in Ecuador in the last twenty years, 59% of which had climatic origin. Additionally, the most common extreme climatic events in Ecuador are flood and drought according to the Centre for Research on the Epidemiology of Disasters-CRED (2015). Sivakumar et al., (2005) mentioned that extreme climatic events have increased both in frequency and intensity, making it more difficult for farmers to maintain their crop productions (Cai et al., 2014; Isch, 2011). These climatic phenomena, which are further accentuated by climate change, are key drivers of economic losses that hit especially Tropic's small rice farmers (Harvey et al., 2014), and are one of the main reasons behind rice cropping area loss in Ecuador (Eymond and Santos, 2013; Poveda and Andrade, 2013). For instance, the 2012-winter's impact census over agriculture (MAGAP, 2012), showed that from 140,000 cultivated hectares analysed, 56,562 ha were entirely destroyed by flood and 24,103 ha were partially damaged by the same event. In this context, risk management mechanisms, such as agricultural insurance, can importantly contribute to reduce rice producers' vulnerability and to protect them against the economic losses driven by climatic extremes.

Agricultural insurance is an effective tool for transferring production risk from farmers to other entities. It allows farmers to meet their credit obligations and minimize the effect of extreme climatic events on their revenue (Xu and Liao, 2014). Moreover, agricultural insurance contributes to maintain farmers in the agricultural business, improve their resilience and preserve food security (Bullock et al., 2017; Patt et al., 2009). In pursuit of these goals, Ecuador started to implement in 2010 conventional insurance through the AgroSeguro system that includes a 60% subsidy of insurance's premium cost (MAG, 2018). This is a multi-peril insurance system that covers some crops, including rice, requiring an in-situ verification in case of disaster occurrence. Under the coverage of this insurance, in case of a generalized extreme event, the insurance company's in situ verification capacity could be exceeded, delaying payouts, and some remote regions could be uncovered. Moreover, (Medina, 2017) suggest that conventional insurance in Ecuador may be inefficient due to asymmetric information that may increase adverse selection and moral hazard. Therefore, even if current AgroSeguro insurance system has importantly supported farmers along the last decade, it is important for the Ecuadorian Government to step forward to the next level in agricultural insurance field to expand the insurance coverage and reduce transaction costs resulting in lower premium prices and a more efficient system.

Among different types of agricultural insurance schemes, index-based insurance (IBI) is a promising tool to provide coverage to large agricultural areas around the world (Mobarak and Rosenzweig, 2013), based on the use of a highly losses-correlated index that avoids the need for field losses verification (Carter et al., 2011). The use of such an index as trigger for indemnity payments reduces significantly the costs for the insurance company in relation to losses verification and payment procedure, and reduces fraud, moral hazard and adverse selection (Barnett and Mahul, 2007; de Leeuw et al., 2014) that are frequent drawbacks of conventional insurance. IBI has been underlined as a feasible and efficient risk management tool (Jensen and Barrett, 2017; Jensen et al., 2018; Takahashi et al., 2016), and several studies demonstrated its successful implementation using weather and vegetation index among small and medium farmers in developing countries (Mcintosh et al., 2013; Mude et al., 2009, among others) that can benefit from lower insurance premiums due to lower implementation costs. In this regard, IBI represents an alternative to conventional insurance in Ecuador, which could be applied by insurance companies and the Government to satisfy the risk management needs of rice producers.

However, the technical, economic and administrative hurdles are significant. A major problem that may arise in the implementation of the IBI is the lack of proper correlation between the index and the losses experienced by farmers in the index influence area (IIA), which is the area for which a defined index is representative (Elabed et al., 2013). This problem, known as basis risk, occurs when some farmers from the pool of insured agents do not receive any compensation even experimenting losses, and some others not being affected are indemnified (Clarke, 2016; Hellmuth et al., 2009). To avoid this, IBI can only be applied over spatially homogeneous areas because its main principle is based on the use of a single

2

index over the IIA. Nevertheless, these conditions of homogeneity are rarely found because agriculture is practiced in heterogeneous areas. To keep basis risk in non-significant levels, index selection and analysis may be crucial, very especially with respect to the way variability within the IIA could influence index values.

Among the indexes used in IBI design, several authors (e.g. Jensen et al., 2018; Rao, 2010) underlined vegetation indexes as options that reduce basis risk and provide reasonably accurate loss estimations, and that can significantly profit from recent advances in remote sensing, geographical information systems, and satellite and drone imagery among others. 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). In line with this, in this research we aim to design an IBI based on NDVI for rice crop in Ecuador that covers farmers against drought and flood events, accounting for variability within the IIA. For this, we build upon previous work developed by Arias et al., (2018) for the rice-producing coastal region of Ecuador that identified agro-ecological homogeneous zones (AHZ), based on topographic, soil, and climatic characteristics using principal components and hierarchical cluster analysis. Within that area, in the Babahoyo canton, two AHZs (*f7 and f15*) were located and their influence over the NDVI in rice cultivation was found significant (Valverde-Arias et al., 2019). For the IBI design, two thresholds in the NDVI values will be defined. The physiologic threshold evidences the occurrence of an extreme climatic event and its impact over rice-crop yield. While, the economic threshold is reached when a moderate climatic event occurs, and its impact over the rice-crop yield is not so deep, letting farmers at least to cover the production costs. For these thresholds, two scenarios are contemplated; the first one considers a differentiated production cost for each AHZ. The second scenario uses the same average production cost for both zones *f7* and *f15*. Then, the damage compensation and the premium cost are calculated for each threshold considering the two scenarios and the AHZs.

2   Materials and methods

This section presents the data and methods followed for the development of an IBI. Starting with a description of the study area location (section 2.1) and data used (section 2.2), section 2.3 explains how we assessed the significance of AHZs impact on NDVI. Then, we estimate the functional relationship between NDVI and rice yield (section 2.4), determine the NDVI thresholds (section 2.5), and we assess risk in each AHZ (section 2.6). Finally, for the design of the IBI contract, in section 2.7 we explain first how indemnities are calculated and how the insurance premiums are estimated considering different zones and different coverages.

2.1   Location of study area

This study is located in South America, Ecuador (Fig. 1 A). Rice production in Ecuador concentrates in the coastal area of the country (see Fig.1 B), very especially in the provinces of Guayas and Los Rios (55% and 37% of rice cropping area respectively during the rainy season). This study focuses on rice cultivation area in the Babahoyo canton, which is one of the main rice producer areas in Los Rios Province (Fig. 1 C), where 84% of the rural population of Babahoyo is involved in agriculture, being rice the main crop in the region with 46,556 ha that represent 45% of the total cultivated area in this canton (IEE, 2009; MAGAP, 2014). The location of Babahoyo in an extensive plain of the Ecuadorian coastal region makes it very vulnerable to flood, and as Valverde-Arias et al., (2018) mentioned in their study this canton is also susceptible to droughts. Therefore, given the importance of rice production in the region's economy and its vulnerability to hazardous climatic events, designing and implementing an IBI that accounts for variability within the area and that provides accurate premium prices and indemnities may importantly contribute to rice producers' welfare and stability.
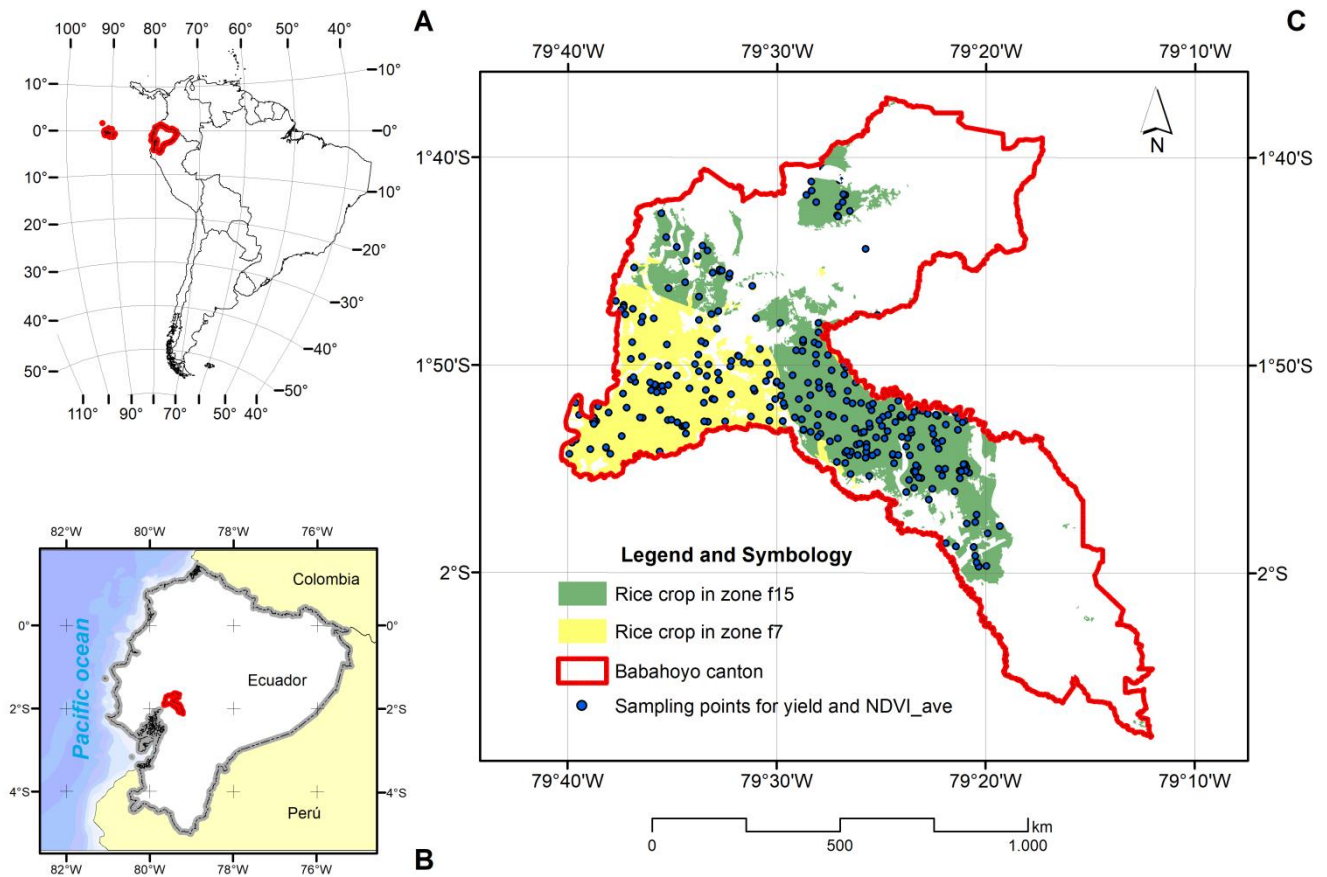
2.2 Cartographic Data

2.2.1 Agro-ecological Homogeneous zones map

In this research we build on the AHZ map generated for the Ecuadorian Coastal region in the study of Arias et al., (2018) that includes our study area (Babahoyo canton). In this map, portions of land with similar agro-ecological characteristics were grouped in homogeneous zones (AHZs) using a statistical method of principal component analysis and a hierarchical cluster analysis. This zoning was evaluated through NDVI imagery in the study of Valverde-Arias et al., (2019), which proved that this zoning is adequate and necessary for designing an efficient IBI, reducing basis risk. According to the map, there are eleven AHZs in Babahoyo, from which seven include rice crop cultivation land. Two of these seven AHZ, *f7* and *f15*, were selected for the study as they account for more than 90% of the total rice-cultivated area in Babahoyo, see Fig. 1 C, in yellow *f7* and green *f17*.

2.2.2 Data from satellite imagery

Satellite imagery data were obtained from the MODIS MOD13Q1V6 product (NASA LP DAAC, 2015) (See Didan et al. (2015) for a description of its characteristics). MODIS imagery was selected due to its long temporal coverage (imagery data available since 2001), which is necessary for constructing a historical sequence of NDVI. MODIS's spatial resolution 250 m is moderate, but for regional applications of crop monitoring this resolution is sufficient (Jiao et al., 2019; Sánchez et al., 2018). Since 2015, Sentinel 2 imagery is available with a resolution of 10 to 60 m depending on the bands. Many studies have used Sentinel for monitoring crops state with very positive results (Inglada et al., 2015; Van Tricht et al., 2018; Veloso

4

135 et al., 2017). However, current time data series availability of Sentinel does not allow its use for IBI design, as at least 10

136 years of historical data are needed for an insurance design (Rao, 2010). Despite this, Sentinel will become in the coming

137 years an important alternative in the insurance field. Also, Sentinel 1, which is a radar sensor, could be an interesting option

138 for rice monitoring in those zones where steadily presence of clouds represent a problem, as Torbick et al., (2017) mentioned

139 in their study.

140 The imagery covers the rice cycle during the rainy season (January to May). There is one image for each 16-day period from

141 2001 to 2017, which makes 170 images in total (17 years x 5 months x two per month). The rice crop cycle in Ecuador takes

142 120 days. The sowing date starts around January 15th, and sometimes it is delayed depending on the onset of the rainy

143 season.

144 The downloaded imagery have a hierarchical data format (HDF), which is a multilayer file (twelve layers) (Didan, 2015);

145 however, we used the layer Hdf:0 that corresponds to NDVI values. Additionally, we used the Quality Assurance layer

146 (quality layer: 250m 16 days VI Quality) included in the HDF file of NDVI MODIS imagery. In this layer, each pixel has a

147 rank key that identifies the pixel quality, the rank key = 0 means good data, use it with confidence. Then, we used only

148 pixels with 0 rank key (Didan et al., 2015).

149 **2.3   Statistical analysis**

150 NDVI values over rice along its crop cycle were analysed for the period 2001 to 2017. NDVI_ave is the average of all NDVI

151 measures of rice crop cycle (January to May) for each observation point. We sampled 30% of the total pixels of rice crop in

152 Babahoyo canton resulting in 31,756 observations: 13,498 in AHZ *f7* and 18,258 in AHZ *f15*. Following Olofsson et al.,

153 (2014) we used equation (1) to calculate the minimum size of the sample. The adequate sample size for this stratified design

154 should be above 12.77% of the total pixels in each stratum (AHZ *f7* and *f15*). Also, Valverde-Arias et al., (2019)

155 demonstrated that a 10% sample was significantly representative in this case. Therefore, 30% is an adequate sampling size

156 that ensures representativeness of the sample.

157 $$n = \frac{(\sum w_i s_i)^2}{[S(\hat{O})]^2 + (\frac{1}{N})\sum w_i s_i^2} \approx \left(\frac{\sum w_i s_i}{s(\hat{O})}\right)^2 \qquad (1)$$

158

159 Where,

160 N is number of the total spatial units in the area of interest (pixels)

161 S(O) is the standard error of the overall accuracy that we would like to achieve

162 Wi is the mapped proportion of area of class i, and

163 Si is the standard deviation of stratum i

164 Descriptive statistics were applied to the NDVI_ave data set, including the normality test of Kolmogorov-Smirnov, which is

165 recommended for more than 50 observations (Razali and Wah, 2011). If the data set fits a normal distribution, an analysis of

166 variance ANOVA will be applied for comparing means of two variability factors (zones and years). Otherwise, we will

167 determine which distribution this data set fits, and the test of Kruskal-Wallis for comparing median of AHZs and years will

168 be used. If significant differences are found among years, the Least Significance Difference (LSD) multiple rank test for

169 means (Williams and Abdi, 2010) or the Bonferroni test for medians will be applied. Years that are not significantly different

170 will be grouped into five categories based on NDVI_ave values: very low, low, normal, high, and very high years.

171 **2.4   Rice-Yield estimation through NDVI_ave**

172 According to Huang et al., (2013) remote sensing products can be used for generating yield estimation models that do not

173 require variables, as crop management or fertilizer applications. Robust results are obtained in rice-yield prediction even at

174   province level. Quarmby et al., (1993) mentioned that rice and maize yields could be estimated accurately by a simple linear

175   regression between NDVI and yield; in addition, Son et al., (2014) suggested that the use of multi-temporal NDVI data for

176   estimating rice-yield in large scale should be a possible and accurate alternative. In this research, we used the normal

177   distribution Eq. (2) for estimating rice yield from NDVI_ave values, quantifying in this way the economic losses in rice

178   cultivation caused by extreme climatic events. The estimation of rice yield was based on the relationship with the NDVI_ave

179   and the crop state.

180    $$Y = \frac{1}{\sigma\sqrt{2\pi}} \; e^{-\frac{(X-\mu)^2}{2\sigma^2}}$$ (2)

181   Where:

182   σ = Standard deviation

183   σ^2 = Variance

184   X = Independent variable (NDVI_ave)

185   Y = Dependent variable (estimated rice yield)

186   μ = Arithmetical Mean of NDVI_ave in years 2016 and 2017

187   The General Coordination of the National Information System (CGSIN-acronym in Spanish-) of Ecuadorian Agricultural

188   and Livestock Ministry (MAG) has conducted a rice-yield estimation project since 2014 when it began sampling yields

189   across mapped rice areas (Moreno, 2014). Thus, 369 georeferenced rice-yield observations (t/ha) were available for 2014-

190   2017 rainfed cycles (January to May) in the study area over AHZs *f7* and *f15* (see, Fig. 1 C). Therefore, we used these rice

191   yield observations with their corresponding spatial and temporal NDVI_ave values for obtaining the parameters included in

192   Eq. (2) (Valverde-Arias et al., 2019). The robustness of this model was evaluated through the RMSE (%) and R-squared

193   coefficient.

194   **2.5   Thresholds determination**

195   There are three different levels of rice crop loss impacts, caused by drought and flood, that should be evaluated based on the

196   vegetation index selected. In the first one, catastrophic impact, the crop is acutely affected, and the farmers cannot recover

197   any part of their investment. In the second level, physiological impact, the crops are strongly affected but farmers can

198   recover part of their investment. Finally, economic impact, the crop loss impact still allows farmers to recover their

199   investment to break-even or have a null profit. To differentiate in these three levels two NDVI_ave thresholds are needed.

200   According to LSD and Bonferroni multiple range tests, years with the lowest NDVI_ave means and medians are selected as

201   the more representative of physiological threshold. Then, we contrast if these years have been actually affected by flood or

202   drought through the climatic application of National Oceanic and Atmospheric Administration (NOAA, 2018). Finally, we

203   verified that these thresholds correspond to the reality comparing the estimated yield obtained using the NDVI_ave

204   thresholds with the expected yields in each AHZ and *cantonal* (at Babahoyo canton level) in normal years.

205   For the economic threshold, we set an NDVI_ave value that let farmers cover at least their production cost. Thus, we

206   considered the sale price at farm gate for a tonne of rice and the production cost in two scenarios: scenario 1 (when we

207   consider differentiated production cost for AHZs *f7* and *f15*) and scenario 2 (non-differentiated production cost for AHZs).

208 According to CGSIN, there are officially three different rice-crop production systems in Ecuador for rainfed agriculture and
209 two for irrigated agriculture in 2017. Each of them has different production costs as shown in Table 1, and they depend on
210 the level of farm modernization and whether they are rainfed or irrigated.

211 **Table 1. Official production cost of different rice-production systems in Ecuador in 2017**

Rice cultivation production cost (USD/ha)				
Rainfed production system			Irrigated production system	
Non-technical	Semi-technical	Technical	Semi-technical	Technical
1022.0	1629.7	1955.9	1631.0	1997.4

212 Source: MAG, (2017)

213 Since, we assessed rice production during rainy season (January-May); irrigation is not required in normal conditions. For
214 this reason, we use production costs of rainfed agro-systems. Among rainfed production systems, we chose the non-technical
215 and semi-technical systems, which are more exposed to suffer the impacts of extreme climatic events, and therefore are the
216 ones that should adopt insurance. We assigned to *f7* the production cost of a non-technical production system (1022 USD/ha)
217 and for *f15* the cost of semi-technical production system (1629 USD/ha) for the scenario one (see Table 1), as according to
218 Valverde-Arias et al. (2019) *f15* has an expected yield higher than *f7*'s yield in regular years that could be explained by *f15*'s
219 better soil conditions and to a more technical production system than in *f7*. Then, when we do not consider AHZs i.e., at
220 *cantonal* level, we used a weighted average production cost of these two systems (1259 USD/ha). In scenario two, i.e. when
221 similar costs are assumed for both AHZ, we used the weighted average (1259 USD/ha) for all the cases (*f7*, *f15*, and
222 *cantonal*).

2.6 Risk assessment in AHZs

224 Once, we found the distribution that fits our data for each AHZ and *cantonal*, we simulated through these distributions a
225 determined number of NDVI_ave values. Then, we compared the frequency of observed NDVI_ave values with the
226 estimated ones. The basis risk of the estimation was evaluated through the Adjusted R-squared coefficient (Vedenov and
227 Barnett, 2004).

228 Lastly, we calculated the proportion of positive events, that is, the number of events equal or under each threshold
229 (physiologic and economic) for each estimated distribution (*f7*, *f15* and *cantonal*). Finally, we tested whether these
230 proportions of *f7* and *f15* are significantly different from each other or not. This analysis was performed through the Z- test
231 of two independent proportions. It consists in contrasting if these two proportions which came from two different
232 populations are equal (Pardo et al., 1998; Polasek, 2013).

  1. Hypothesis:

    $H_0: p_1 = p_2$; $H_1: p_1 \neq p_2$

  2. Postulation: the studied variable (NDVI_ave) is dichotomous (below/equal or above the threshold) in these two
    populations (*f7* and *f15*). From these two populations, two random samples were extracted independently with
    n_1 and n_2 sizes. These samples had p_1 and p_2 success probability, which are constant in each extraction. Positive
    events occur when the observation is equal or below the threshold.

  3. Contrast statistics:

    Sample *f7*: n_1, P_1; where n_1 = population of *f7* and P_1 = ratio of positive events
    Sample *f15*: n_2, P_2; where n_2 = population of *f15* and P_2 = ratio of positive events

243 $$P = \frac{n_1 P_1 + n_2 P_2}{n_1 + n_2} \tag{3}$$

244

245 $$Z = \frac{P_1 - P_2}{\sqrt{P(1-P)\left(\frac{1}{n_1} + \frac{1}{n_2}\right)}} \tag{4}$$

246

247   4.   Critical ratio

248

249   Bilateral:

$$Z \le {}_{\propto/2}Z$$

250 $$Z \ge {}_{1-\propto/2}Z$$

251   5.   Decision. - Reject H_0 if contrast statistics falls in critical rate or $p \le \propto$

252 **2.7   Insurance contract design**

253 **2.7.1   Indemnity calculation**

254 The indemnity is the amount of money that an insured individual receives when a covered hazard occurs. In this case, we

255 have two insurance policies options. The first one is the working capital, where the insured amount corresponds to the

256 money necessary for recovering the investment (production cost) that a farmer has spent. The second one is the profit (gross

257 margin), where the insured amount is the money that a farmer would obtain selling his production after covering his

258 production cost in a normal year.

259 In other words, for the first option the compensation will cover the yield reduction between the economic and physiologic

260 threshold. In the second case, the compensation will cover the difference between the expected yield in a normal year and the

261 yield obtained at the economic threshold.

262 Thus, the indemnity calculation follows the next equation (Maestro et al., 2016):

263 $$I_{sz} = Y_z \times P - Pc_{sz} \tag{5}$$

264 Where:

265 I_{sz} is the net income expected per hectare (USD/ha) in a normal year, differentiated by *s* scenario (it could be 1 or 2), and *z*

266 zone (*f7, f15* or *cantonal*).

267 Y_z is the expected yield (tones/ha), in normal years for *z* zone.

268 *P* is the price of a ton of rice at farm (USD/t).

269 Pc_{sz} is the production cost per hectare of rice cultivation (USD/ha), differentiated by *s* scenario (it could be 1 or 2), and *z*

270 zone (*f7, f15* or *cantonal*).

271 Y_z is obtained applying Eq. (1), *P* was calculated from rice price monthly variation along the last two years. This value is

272 assumed to be constant (371 USD/t) for both AHZs and *cantonal*, and for scenario 1 or 2.

273 To estimate Pc_{sz}, we evaluated two scenarios. Scenario 1, with production costs differentiated for each *z* zone (*f7, f15* or

274 *cantonal*); and scenario 2, with the same production costs for all *z* zones (*f7, f15* or *cantonal*).

275 **2.7.2 Premium determination**

276 The commercial or loaded premium cost CP_{sz} is equal to the net premium multiplied by a factor that covers the insurance

277 company profit and loading cost. The net premium or risk premium NP_{sz} has to cover the expected compensations that an

278 insurance company would have to pay during the analysed period. The net premium is calculated as a percentage of I_{sz}. This

279 percentage corresponds to the probability that the insurance company have to compensate I_{sz} in a period of time

280 (Jasiulewicz, 2001; van de Ven et al., 2000). It was expected that the probability of occurrence is different for each AHZ (*f7*

281 and *f15*). It is also different when the NDVI_ave measure is made at *cantonal level*. Thus, we calculated differentiated

282 premium rates for each one of these cases.

283 $$NP_{sz} = I_{sz} \times Pr_{sz} \qquad (6)$$

284 $$CP_{sz} = NP_{sz}(1 + (\beta_1 + \beta_2)) \qquad (7)$$

285 Where:

286 NP_{sz} is net premium rate (USD/ha) for scenario *s* (scenario 1 or 2) and *z* zone (*f7, f15* and *cantonal*).

287 CP_{sz} is commercial premium rate (USD/ha) for scenario *s* (scenario 1 or 2) and *z* zone (*f7, f15* and *cantonal*).

288 Pr_{sz} is the probability of sinister occurrence for *s* scenario (scenario 1 or 2) and z zone (*f7, f15* and *cantonal*).

289 β_1 is the insurance company profit (20% of NP_{sz}).

290 β_2 is the operative cost of the insurance plus taxes (5% of NP_{sz}).

291 The commercial premium value CP_{sz} in index-based insurance is generally subsidized by the government in around 60% to

292 small farmers in developing countries (Peter Höppe, 2007; Ricome et al., 2017).

293 **3 Results and discussion**

294 **3.1 Statistical analysis**

295 From descriptive statistical analysis, the kurtosis (0.56) and a skewness (-0.78) indicated that the data set of NDVI_ave fits a

296 normal distribution; however, the Lilliefors (Kolmogorov-Smirnov) normality test showed: D = 0.080207 and a p-value <

297 $2.2e^{-16}$ lower than 0.05; then we rejected the null hypothesis because the data set does not come from a normal distribution.

298 We have found that our data fits a Generalized-minimum extreme value (GEVmin) distribution (Kotz and Nadarajah, 2000)

299 for the *cantonal* data set and for the two AHZs (*f7* and *f15*) based on χ^2 statistics (Table 2).

300 **Table 2. Parameters of Generalized-minimum extreme value (GEVmin) distribution for each AHZ and cantonal and distribution**

301 **adjustment statistic of maximum likelihood**

	Mode	Scale	n	k	F.D. (n-1)x(k-1)	Chi-squared table	Chi-squared calculated
Cantonal	0.52	0.09	100	11	990	1064.31	9.42
f7	0.51	0.11	100	11	990	1064.31	2.75
f15	0.53	0.08	100	10	891	961.55	2.16

302 Because the data sets did not fit normal distributions, we used a non-parametric test to determine if NDVI_ave medians in

303 zones *f7* and *f15* are significantly different. The Kruskal-Wallis test for these zones (χ^2 = 345.48, F.D. = 1, p-value < 2.2e-

304 16) shows us that the null hypothesis of *f7* and *f15* being equal can be rejected because the p-value is lower than 0.05. The

same test mentioned before shows us that years are also significant different (χ^2 = 7507.4, F.D. = 16, p-value < 2.2e-16 is also lower than 0.05). Five categories in years are established when LSD (Mean) and Bonferroni (Median) test are applied on NDVI_ave values (see Table 3).

Table 3. Fisher`s Least Significant Difference (LSD) test for comparing means, and Bonferroni test for comparing medians, for years

Year	Mean (NDVI_ave)	Year	Median (NDVI_ave)	Category
2008	0.39	2008	0.39	*Very low* (Years affected by extreme climatic events)
2012	0.40	2013	0.42	
2013	0.40	2016	0.43	
2016	0.40	2012	0.43	
2017	0.42	2017	0.44	*Low* (Years affected by moderate climatic events)
2014	0.42	2014	0.45	
2015	0.45	2010	0.47	
2010	0.46	2015	0.48	
2002	0.48	2011	0.48	*Normal* (Normal years)
2005	0.49	2005	0.49	
2011	0.49	2002	0.49	
2001	0.51	2001	0.52	*High* (Years with good climatic conditions)
2009	0.51	2009	0.52	
2007	0.52	2007	0.52	
2003	0.54	2004	0.54	*Very High* (Years with very good climatic conditions)
2004	0.55	2003	0.55	
2006	0.55	2006	0.56	

3.2 Rice yield estimation

The observed rice yield was plotted versus NDVI_ave in a rice crop cycle. A normal accumulative curve was adjusted, see Eq. (2) in Fig. 2 A, to relate both variables; where μ (0.49) is the mean of NDVI_ave measured in yield sampling points of years 2014 through 2017; σ (0.14) is the standard deviation, and X is the NDVI_ave value for which, we want to estimate rice yield (Y). The RMSE (%) of 3.3 and an R^2 of 0.71 indicate a robust model. This type of curve was selected, instead of a linear regression, to take into account the high values of the NDVI saturation effect on plant biomass (Gu et al., 2013) and the soil saturation effect on low NDVI values (Rondeaux et al., 1996). The correlation coefficient of observed versus estimated rice-yield was high (0.89), showing that NDVI_ave is an adequate indicator for assessing the impact of drought and flood over rice crop (Fig. 2 B).
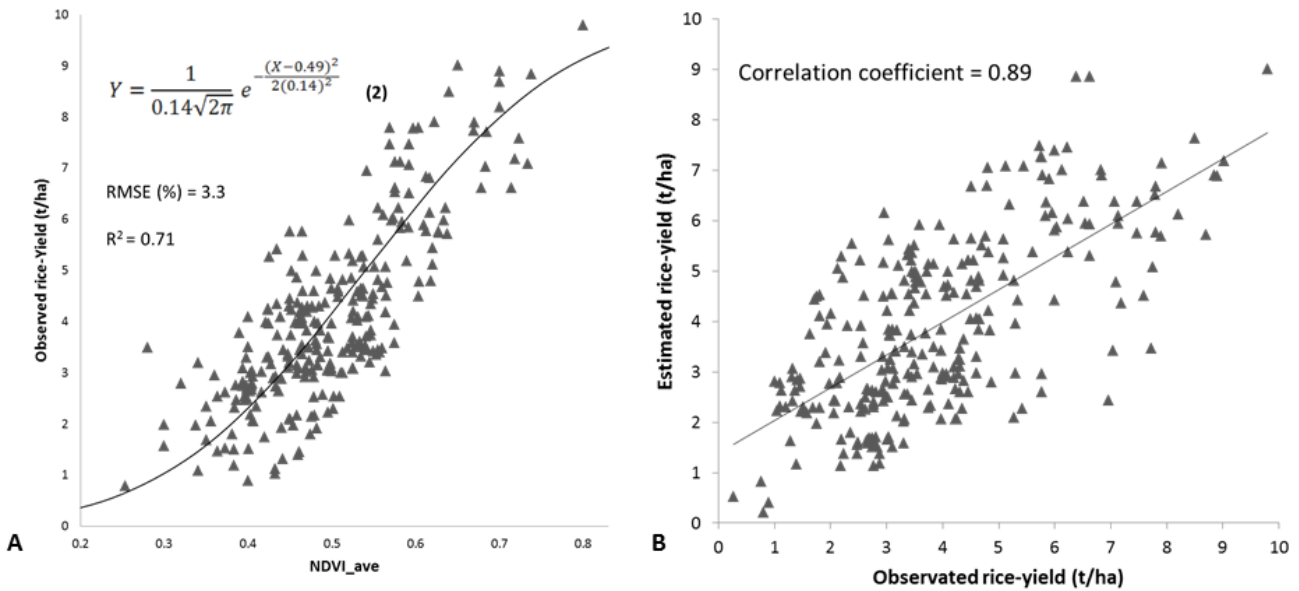
Figure 2. A) Scatter plot of observed rice-yield and NDVI_ave, curve of Eq. (2) for estimating yield (Valverde-Arias et al., 2019); and B) correlation of observed and estimated rice-yield
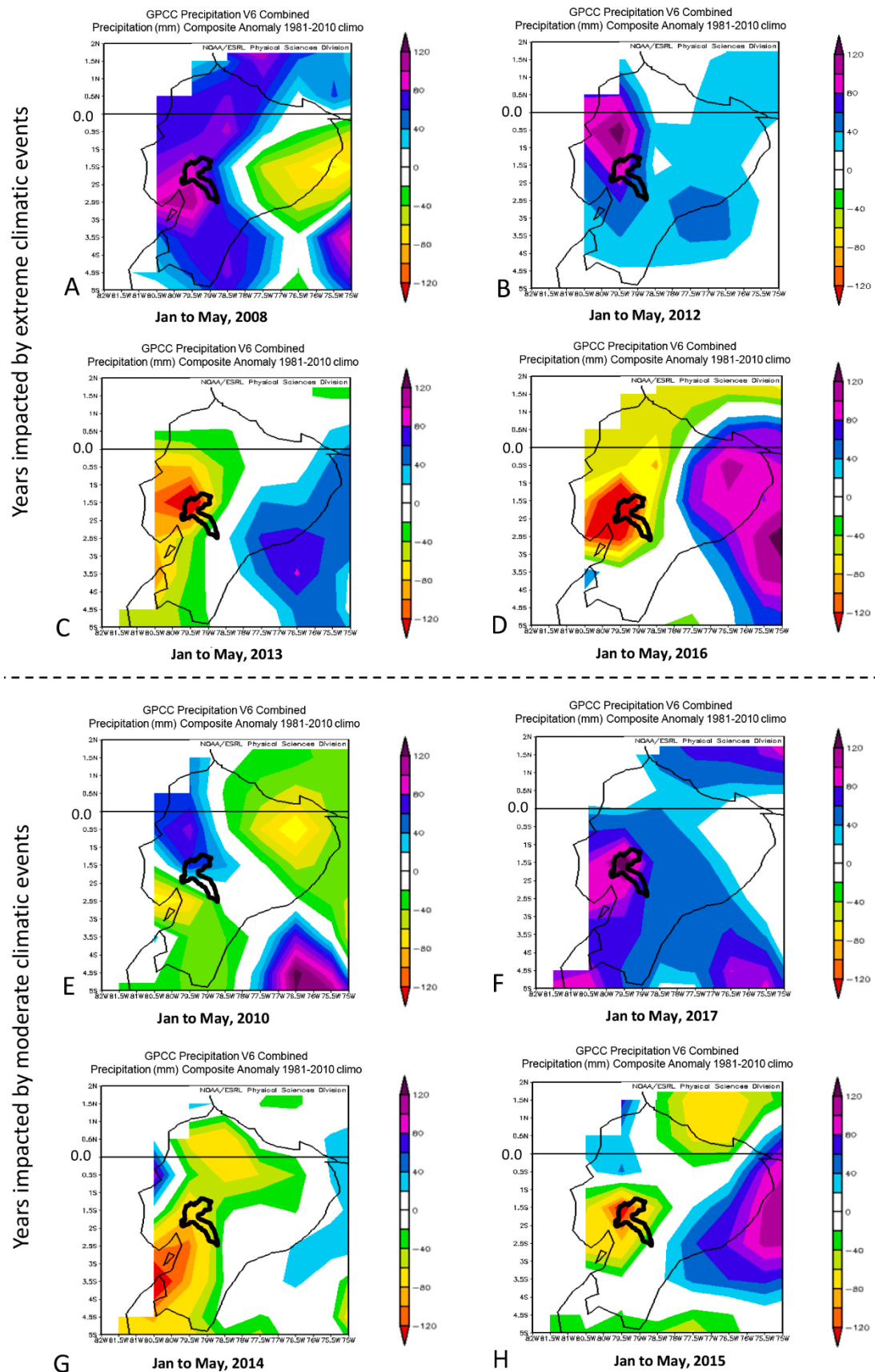
3.3 Thresholds determination

Since that the years have been classified in five categories, we could define the different levels of impact or no impact over rice crop (NDVI_ave), as shown in Table 3. When rice yield is less than 0.5 t/ha (NDVI_ave ≤ 0.26), due to damage in rice crop by extreme events, the total loss threshold is neither detectable at cantonal level nor at AHZs (*f7* and *f15*) level. Individual NDVI_ave observations equal or under the total losses' threshold can be found but not as a regional measure of NDVI_ave. However, in our IBI design the index measure is an average of all observations within a homogeneous zone, being these *cantonal* or AHZs (*f7* and *f15*).

The physiologic threshold represents the maximum rice-crop damage that can be detected through NDVI_ave at regional scale, which has been caused by an extreme climatic event. It is fixed (0.4) for both AHZ (*f7* and *f15*) and cantonal (see Table 4). The years when we reached the physiologic threshold in our data set were 2008, 2012, 2013, and 2016. These years belong to the "very low category"; and according to climatic application (NOAA, 2018) these years were affected by extreme climatic events. This application contains and plots historical climatic data. In this case, we analysed the combined precipitation anomalies. Zero represents no precipitation anomaly, i.e. average precipitation; positive anomalies occur in years that precipitation is above the average (floods) and negative anomalies when the precipitation is below the average (drought). As we can see in Fig. 3 A and B; Babahoyo canton presented positive anomalies of precipitation (floods) in 2008 and 2012 and negative anomalies of precipitation (drought) for 2013 and 2016 (Fig. 3 C and D).

Table 4. Different categories of impact thresholds for scenarios of differentiated and non-differentiated production costs

	Differentiated production cost (Scenario 1)						Non differentiated production cost (Scenario 2)						Occurrence verification by	Type of Insurance	
	Cantonal		*f7*		*f15*		*Cantonal*		*f7*		*f15*			*IBI*	*Conventional*
	NDVI _ave	Yield (t/ha)	NDVI _ave	Yield (t/ha)	NDVI _ave	Yield (t/ha)	NDVI _ave	Yield (t/ha)	NDVI _ave	Yield (t/ha)	NDVI_ ave	Yield (t/ha)		Compensation for	
Expected Yield	0.51	5.65	0.49	5.11	0.55	6.68	0.51	5.65	0.49	5.11	0.55	6.68	Index	NSC	NSC
Economic Threshold	≤0.43	3.39	≤0.41	2.75	≤0.47	4.39	≤0.43	3.39	≤0.43	3.39	≤0.43	3.39	**Index**	**Profit**	**NSC**
Physiological Threshold	≤0.40	2.65	≤0.40	2.65	≤0.40	2.65	≤0.40	2.65	≤0.40	2.65	≤0.40	2.65	Index/in-situ	Profit	Investment
Total losses	≤0.26	≤0.5	≤0.26	≤0.5	≤0.26	≤0.5	≤0.26	≤0.5	≤0.26	≤0.5	≤0.26	≤0.5	In-situ	No detectable	Investment

IBI (index-based Insurance); NSC (not susceptible of compensation)

On the other hand, the economic threshold depends on economic factors such as sale rice price and production cost. These are not constant and must be set regarding the necessary yield for covering the farmer's expenses during the rice cultivation campaign, as it is shown in Table 4.

The economic threshold represents the minimum yield that farmers must reach for covering at least the production cost. It is higher than physiologic threshold, and it varies according to the scenario. In scenario 1, the economic threshold is different for each AHZ (*f7* and *f15*); *f7*'s being lower production cost (1022 USD/ha) than that for *f15* (1629 USD/ha). Thus, the economic threshold of *f7* is 0.41, while for *f15* is 0.47 (see Table 4). The years from our dataset that reached the economic threshold were 2010, 2014, 2015 and 2017. They were impacted by moderate climatic events (flood for 2010 and 2017 and drought for 2014 and 2015) according to NOAA (2018), see Fig. 3 E, F, G and H.

For scenario 2, the production cost is a weighted average (1259 USD/ha) both for AHZs (*f7* and *f15*) and cantonal. Therefore, the economic threshold (0.43) is the same for AHZs and *cantonal*, see Table 4.

3.4   Risk assessment of AHZ and Babahoyo canton

The risk status of *f7* and *f15* were found to differ based on the following results. We found that 25% of events under the physiologic threshold for *f7* and 17% for *f15* (see Fig. 4 B, C); and when we do not consider AHZs (*cantonal*) 21% (Fig. 4 A). AHZ *f7*'s probability is higher because of its soil conditions (see Table 5). These conditions make the zone more vulnerable to floods due to its very fine texture (>60% clay), flat lands (0-5% slope), very low altitude (1-12m) and proximity with rivers' banks that contribute to very poor drainage of this zone. In the same way, these characteristics could give to *f7* better capacity for long-term water retaining, during a drought. However, when drought is extreme, the *f7*'s soil (Vertisol) gets very dried (Soil Survey Staff, 2014); consequently, it becomes very hard and develops deep cracks. This phenomenon affects physically the crop's roots and hinders considerably the soil tillage (Valverde-Arias et al., 2019).

Table 5. Soil and climatic characteristics of Agro-ecological homogeneous zones AHZs in Babahoyo Canton

	Zone *f7*	Zone *f15*
Slope	0-5%	5-12%
Altitude	1-12m	12-35m
Clay	>50%	35-50%
Effective depth	50-100 cm	>100 cm
pH	5.6-6.5	6.6-7.4
Organic matter	2-4%	2-4%
Temperature	24-25 ºC	24-25 ºC
Precipitation	500-700 mm/year	700-900 mm/year
Soil Classification*	Typic Hapluderts	Vertic Eutrudepts

Source: (Valverde-Arias et al., 2019); *According to USDA Soil Taxonomy (Soil Survey Staff, 2014)
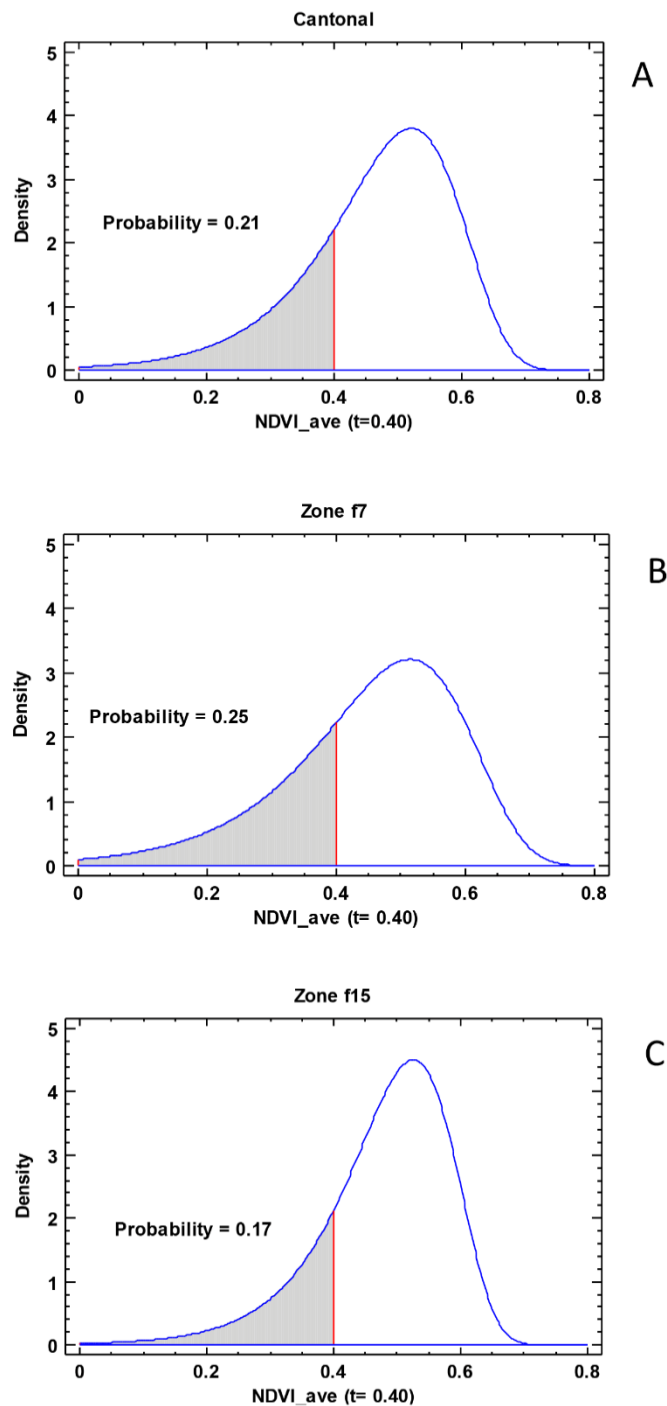
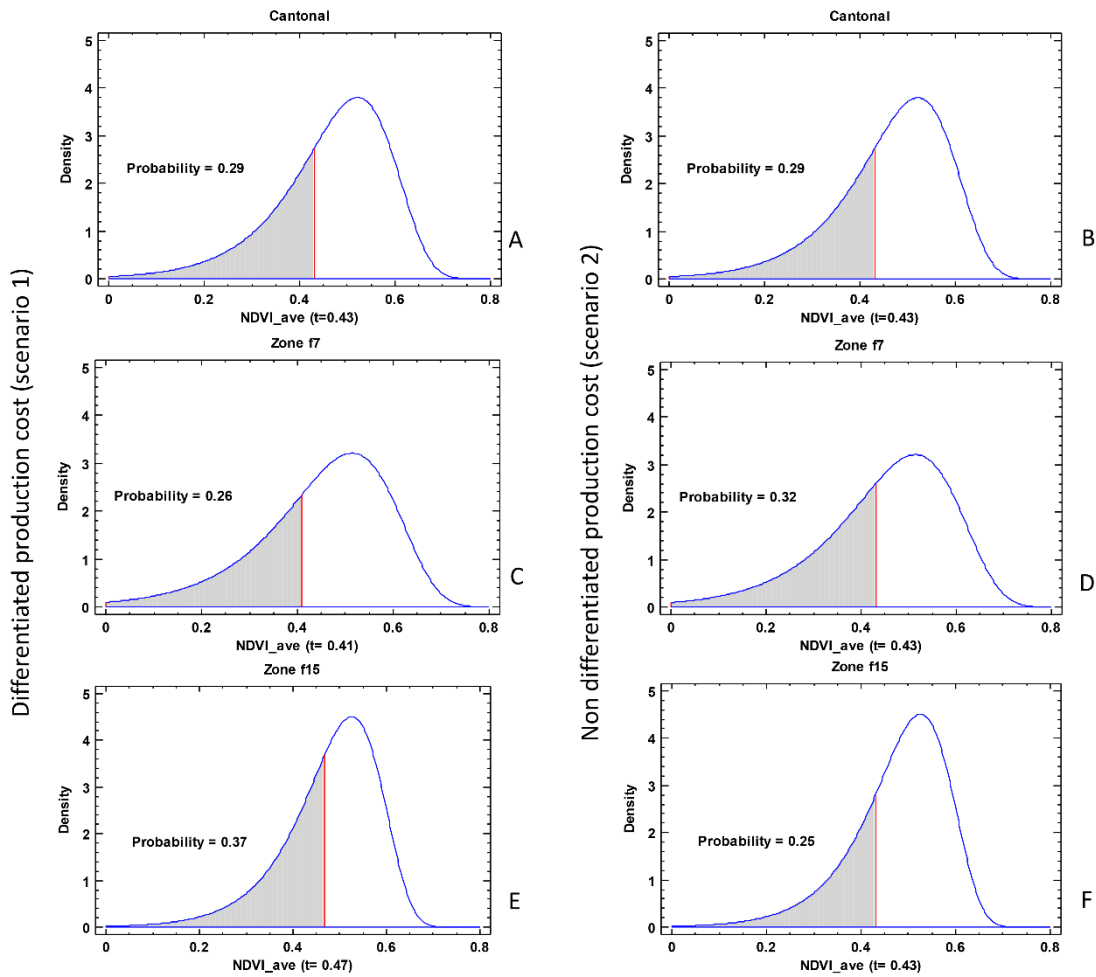**Figure 4. Physiologic threshold (red line) within Generalized-minimum extreme value (GEVmin) distribution of NDVI_ave; (A) cantonal, (B) *f7* and (C) *f15* zones**

For economic thresholds, we also found differences between the risk status of AHZs *f7* and *f15*. Furthermore, for scenario 1, the probability of having events equal or under the economic threshold is higher in *f15* (37%) than that in *f7* (26%) and that in *cantonal* (29%), as we can see in Fig. 5 A, C and E. The reason for this is that in this scenario, *f15*'s farmers have to cover a higher production cost (which corresponds to semi-technical production system), and, therefore, they have to reach an economic threshold also higher (0.47) than that one in the *f7*.

Figure 5. Economic threshold (red line) within Generalized-minimum extreme value (GEVmin) distribution of NDVI_ave for differentiated production cost (scenario 1) for: (A) *cantonal***, and Agro-ecological homogeneous zones (C)** *f7* **and (E)** *f15***; and for non-differentiated production cost (scenario 2) for: (B)** *cantonal***, and Agro-ecological homogeneous zones (D)** *f7* **and (F)** *f15*

In scenario 2, the economic threshold is equal (0.43) for *f7*, *f15* and *cantonal*, but the probability to find events under the threshold is higher in *f7* (32%) than that in *f15* (25%) and that in *cantonal* (29%). Although the economic threshold is the same for both AHZs (*f7* and *f15*) and at *cantonal* level, in this scenario, the frequency distributions of NDVI_ave were different for each zone. Consequently, they accumulated different probabilities under the same threshold, as shown in Fig. 5 B, D and F.

At this point, we evaluated the Z-test results for determining if the found differences have statistical significance. Based on the Z-test (see Table 6), the null hypothesis ($H_0: p_1 = p_2$) can be rejected in both scenarios 1 and 2, so we can assert that the proportion of positive cases (equal or under physiologic and economic thresholds) in *f7* are significantly different from that in *f15*. For economic threshold in scenario 1 (differentiated production cost), the calculated Z is negative because in this case the probability in *f15* is higher than in *f7*.

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Table 6. Z-test for probability of events susceptible of compensations ESC under physiologic and economic thresholds in Agro-ecological homogeneous zones (*f7* and *f15*) and cantonal

	Type of threshold	Observations	Positive events	Probability	Critical rate	Z test
Non differentiated production cost/ differentiated production cost	*Physiological threshold cantonal*	31,756	6669	0.21	Z≤ z_0.025= -1.96 Z≥z_0.975=1.96	**18.06**
	Physiological threshold f7	13,498	3375	0.25		
	Physiological threshold f15	18,258	3041	0.17		
Differentiated production cost (scenario 1)	*Economic threshold cantonal*	31,756	9209	0.29	Z≤ z_0.025= -1.96 Z≥z_0.975=1.96	**-21.35**
	Economic threshold f7	13,498	3510	0.26		
	Economic threshold f15	18,258	6756	0.37		
Non-Differentiated production cost (scenario 2)	*Economic threshold cantonal*	31,756	9209	0.29	Z≤ z_0.025= -1.96 Z≥z_0.975=1.96	**13.59**
	Economic threshold f7	13,498	4320	0.32		
	Economic threshold f15	18,258	4565	0.25		

As NDVI_ave dataset fits a GEVmin distribution, we used this distribution, with its specific parameters (Mode and Scale, shown in Table 2) for estimating NDVI_ave density frequencies for *f7*, *f15*, and *cantonal*. With these distributions, we calculated the positive events under physiological and economic thresholds in scenarios 1 and 2. Then, we estimated the basis risk of these calculations. In this case, basis risk could arise if the estimated distribution does not fit properly with the distribution observed from measured data.

We have found that the basis risk for this estimation is negligible according to Adjusted R-squared shown in Fig. 6 A, B and C. Therefore, we can confidently use these estimations for determining the events proportion that reached the physiologic and economic thresholds, i.e. the occurrence probability of extreme events that warrant compensations.
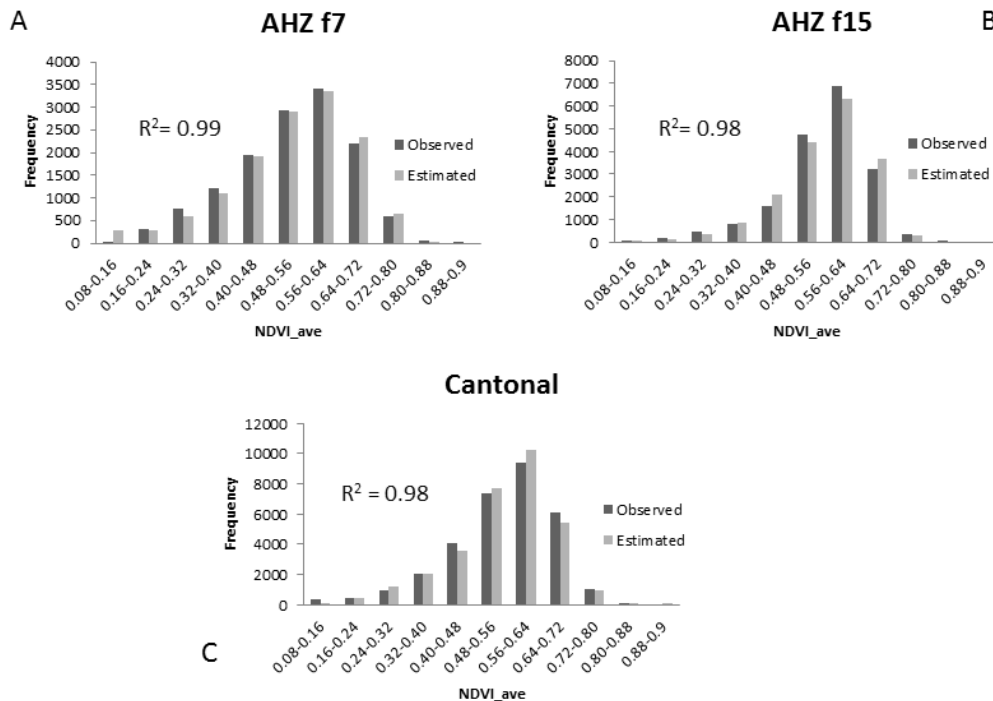
Figure 6. Frequency distribution of NDVI_ave values both observed in imagery data and estimated through GEVmim distribution in: A) *f7*, B) *f15* and C) *cantonal*

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3.5 Indemnity calculation

The indemnity for farms that reach the physiological threshold in scenario 1 is reported in Table 7. These values show us the deficit (negative numbers) that farmers face for recovering their production costs when their crop yield falls below the break even, in each AHZ (*f7* and *f15*) and *cantonal*. The indemnity would make up the difference between crop's costs and revenue in case of extreme event. In *f7* the indemnity would be 38 USD/ha, it means that when a farmer reaches physiologic threshold, he only lacks 38 USD/ha for covering his production cost. A farmer from this scenario could dispense with the insurance contract, because the deficit to hit the break-even is not representative. On the contrary, when *f15* reaches the physiologic threshold, its deficit is very high (645 USD/ha), which is the money that an *f15*'s policyholder would receive as compensation in case of an extreme event occurrence.

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**

*= Yield at Physiologic threshold, for Economic threshold it is the yield reached in regular years, ** = Differentiated production cost and *** = Non differentiated production cost

For scenario 2 of physiological threshold, the indemnity would be 275 USD/ha for all AHZ (*f7* and *f15*) and for *cantonal*, due to their same production cost (1259 USD/ha). As was mentioned before, in Ecuador, currently, it exist an agricultural conventional insurance that covers the rice growers' working capital; but we included this calculation as an alternative to conventional insurance or for these areas where conventional insurance is not feasible.

When looking at the economic threshold, as we can observe in Table 7, the indemnity (Gross Margin) in scenario 1 is very similar between AHZs (*f7* and *f15*) and *cantonal* though their expected yields are different. This is because their assigned production cost has been related with their expected yield. For example, since farmers have invested more money in their crop in *f15*, their expected yield is higher. Moreover, the difference in the premium price of these zones will be determined by the different probability of extreme events occurrence in each AHZ (*f7* and *f15*) and *cantonal*.

In scenario 2, on the other hand, we have assumed the same production cost for *f7* and *f15*; thus, *f15* has higher expected yield in normal years than *f7*. Obviously, in this scenario *f15* obtains the highest gross margin (1223 USD/ha), having also the highest compensation, which would be reflected in a higher premium cost. However, *f7* has the lowest insured amount (640 USD/ha), so that its premium cost should be low. But we have to consider that premium cost calculation also depends on the occurrence probability of the insured event.

For economic threshold, the indemnity calculation (840 USD/ha) for *cantonal* is equal in both scenarios 1 and 2, as shown in Table 7; because, we used the same weighted average as production cost (1259 USD/ha). For *f7* it is expected a higher gross margin in scenario 1 than that in scenario 2, due to scenario 2's production cost being higher. On the contrary, for *f15* the

gross margin is higher in scenario 2 than that in scenario 1; because in scenario 2, *f15* has lower production cost than in scenario 1.

3.6   Premium determination

The premium value is related to the insured amount (the indemnity or compensation that insurance company must pay to farmers when an insured extreme event occurs), and the probability of the ensured extreme event occurs in a determined period. Table 8 shows the net and commercial premium calculation for the two different thresholds under both scenario1 and scenario 2, and for each AHZ and at *cantonal* level.

In general terms, it can be appreciated that premium cost for economic thresholds are more expensive than that for physiologic threshold, in both scenarios (1 and 2). This is because the insured amounts for economic threshold are higher than that for physiologic threshold. In the first case, the compensation covers the entire lost profit; while in the second one, the compensation covers only the deficit necessary for recovering the investment (production cost).

If the insured amounts are similar among AHZs (*f7* and *f15*) and *cantonal*, the difference among premium costs is determined by the occurrence probability. However, when there are sharp differences among insured amounts of AHZs (*f7* and *f15*) and *cantonal*, these influence more the premium cost variation than the occurrence probability.

Moreover, for physiologic threshold in scenario 1, the premium cost is determined mainly by the insured amount, for instance, for *f15* the premium cost is the highest (136.98 USD/ha) despite of its occurrence probability being the lowest. On the contrary, for *f7* its premium cost is very low, despite its highest occurrence probability, because of having a greater insured amount.

While under economic threshold in scenario 1, the insured amount of AHZs (*f7* and *f15*) and *cantonal* are similar, the premium cost for *f15* is the highest (394.66 USD/ha), due to its highest occurrence probability.

When costs are not differentiated across AHZ (scenario 2), for the physiologic threshold the insured amount is equal in all AHZs (*f7* and *f15*) and *cantonal*, and thus their premium cost has been differentiated through the occurrence probability, being the highest for *f7* (85.82 USD/ha). In the same scenario, for the economic threshold *f15* has the highest gross margin, and therefore a high-insured amount despite its low occurrence probability (0.25). It has a high premium price (382.29 USD/ha), but it is lower than in scenario 1 (394.66 USD/ha) where the occurrence probability is the highest (0.37).

As it can be appreciated in Table 8, after we divided the study area through AHZs map in *f7* and *f15* zones, we can perform more accurate calculations and reduce basis risk of the premium costs according to the expected yield, insured amount, and occurrence probability of each AHZ (*f7* and *f15*). This means that by differentiating the study area through AHZs, we can design an accurate insurance policy where farmers from each zone pay a premium that corresponds to the risk that they are facing. To illustrate this, for physiological threshold in scenario 1, if we do not divide Babahoyo canton through AHZs and instead use *cantonal* as IIA, an average Babahoyo's producer (≈20 ha) from *f15* would pay only 72.09 USD/ha as insurance premium. But if an extreme event occurs, he would receive as compensation only 4915.68 USD which is less than half of the actual loss in a year that an extreme event occurs (11,796.56 USD). At the same time, for the same threshold and scenario, farms from *f7* would pay a much lower premium (11.76 USD/ha), and in case of disaster receive a small compensation which is adjusted to the actual losses experienced by the farmers. This can be of great relevance, as if we assume that farms in *f7* are non-technical production systems that achieve lower yields and get lower economic returns, providing access to affordable insurance with fair premium prices may importantly contribute to expand insurance uptake and reduce substantially socio-economic vulnerability in this area.

Table 8. Calculation of commercial premium rate for physiologic and economic thresholds in scenarios 1 and 2 and for AHZ (*f7* and *f15*) and *cantonal*

Threshold type	Zone	Threshold value	Insured amount (USD/ha)	Occurrence probability of IEE	Net premium cost (USD/ha)	Commercial premium cost (USD/ha)	Production cost + subsidized premium cost (USD/ha)	Compensation to a policy holder /ha (USD)*	Compensation to a policy holder of a farm of 20 ha (USD)*
				Scenario 1 (Differentiated production cost)					
	Cantonal	0.40	274.62	0.21	57.67	**72.09**	1287.83	245.78	4915.68
Physiologic	*f7*	0.40	37.62	0.25	9.4	**11.76**	1026.70	32.92	658.32
	f15	0.40	644.62	0.17	109.59	**136.98**	1683.79	589.83	11,796.56
	Cantonal	0.43	840.21	0.29	243.66	**304.58**	1380.83	718.38	14,367.56
Economic	*f7*	0.41	877.28	0.26	228.09	**285.12**	1136.05	763.23	15,264.64
	f15	0.47	853.31	0.37	315.73	**394.66**	1786.86	695.45	13,908.92
				Scenario 2 (Non differentiated production cost)					
	Cantonal	0.40	274.62	0.21	57.67	**72.09**	1287.83	245.78	4915.68
Physiologic	*f7*	0.40	274.62	0.25	68.65	**85.82**	1293.33	240.29	4805.84
	f15	0.40	274.62	0.17	46.68	**58.36**	1282.34	251.28	5025.52
	Cantonal	0.43	840.21	0.29	243.66	**304.58**	1380.83	718.38	14,367.56
Economic	*f7*	0.43	640.28	0.32	204.89	**256.11**	1361.44	537.84	10,756.72
	f15	0.43	1223.32	0.25	305.83	**382.29**	1411.91	1070.40	21,408.08

476 * In a year when an ensured extreme event (drought and flood) occurs, 20 ha is the average size of a rice-farm in Ecuador

477 Yet, the price of the premium could be expensive for some farmers, but we must consider that this insurance will cover both
478 of the most frequent and intense extreme events that affect Babahoyo canton (drought and flood). For example, for the
479 economic threshold in scenario 1, the premium cost without subsidy would reach the 22% of the total production cost of a
480 policy holder of *f7* and the 20% for *f15*. This means that subsidizing premium cost may still be necessary in order to
481 incentivize the insurance contract taking (Garrido and Zilberman, 2008; Yuanchang and Jiyu, 2010), and the Government
482 subsidy of 60% of the premium cost that it is currently offered in Ecuador with the conventional insurance would still be
483 required.

484 Furthermore, if Government would apply prevention policies to promote farms' modernization, farmer's technical training,
485 and civil works the occurrence probability of extreme events could be reduced or at least mitigated. For instance, dams and
486 irrigation infrastructure could improve the risk status of Babahoyo's farmers facing drought and floods. Consequently, it
487 could be reflected in an insurance premium price reduction.

488 **4   Conclusions**

489 Floods and droughts are a major threat for rice production in Ecuador that undermine food security and endanger
490 sustainability of rural livelihoods in many areas of the country. Risk management mechanisms, such as agricultural
491 insurance, may play an important role in stabilizing production and contributing to reduce the vulnerability of rice farmers.
492 In this context, IBI is a promising tool that facilitates the implementation of agricultural insurance and reduces operational
493 and transaction costs. However, basis risk may lead to inadequate premium prices and to unfair indemnity calculations and
494 payment. To avoid this, the identification of an adequate index and a proper knowledge of variability within the IIA are
495 crucial.

In this research, we developed an IBI based on NDVI_ave that accounts for variability across the insured area. For this, we considered AHZs as the starting point for risk assessment and indemnity calculation and compared it with the insurance design at cantonal level. Two levels of climatic impact over rice cultivation have been identified. The first one is the physiological impact that is determined by a physiological threshold when a climatic event is extreme, its policy contract will cover losses related to the rice grower's working capital. The second level is the economic impact when the climatic event is moderate, and its policy will cover the crops' gross margin.

The results of the analysis performed evidence that the two AHZs show significantly different risk profiles for physiologic and economic thresholds. Therefore, the design of differentiated premium calculation based on the risk status and insured amount of each AHZ ($f7$ and $f15$) will facilitate that farmers pay a fair insurance premium. This insurance premium would be as consistent as possible with their risk status and would help them to receive compensations that effectively cover the totality of their losses.

The basis risk arising from modelling the risk frequency of drought and flood events in Babahoyo (cantonal) and in AHZs ($f7$ and $f15$) through GEVmin distribution is negligible. The basis risk associated with the spatial heterogeneity of Babahoyo canton has been reduced in our IBI design. We have accomplished this by dividing this canton into $f7$ and $f15$ homogeneous zones which have a significant different risk status, different expected yields and may have also different production costs. Considering all these factors and the two different impact levels in the IBI design have allowed to set up a fair premium, reducing in this way the possible bias caused for not discriminating Babahoyo variability.

The cost for contracting an insurance policy could be expensive in some cases. However, the fact that this kind of insurance is generally partially subsidized by the government in developing countries (as Ecuador) could make this insurance affordable to farmers. Moreover, even if the premium price may be high, the index design guarantees to policyholders that the premium price is fair and proportional with the risk they are facing.

The implementation of IBI for rice crop in Babahoyo could let Ecuadorian Government to respond efficiently and rapidly in the case of an extreme climatic event, paying compensations faster than with the conventional insurance. It could stabilize rice-producer incomes and reduce small farmers' vulnerability by providing access to insurance through premium and indemnities adjusted to the specific risk and technology conditions. Consequently, it can incentivise rice cultivation to the desirable levels for covering national demand ensuring food security of Ecuador.

Finally, it is worth mentioning that even if the IBI has been defined for rice crop in a particular area, the methodology applied for developing such an insurance scheme can be applied for other crops and regions if the data to define AHZs, NDVI distributions, crop yield and cost productions are available. This is, therefore, a promising approach for defining IBI schemes minimizing basis risk, which can importantly profit from current advances in remote sensing, satellite imagery and improved information systems.

Author contribution

Omar Valverde has developed the research idea and wrote the original draft of the manuscript, guided and supervised by Alberto Garrido, Ana Tarquis and Paloma Esteve. Ana Tarquis has contributed with the imagery and statistical analysis and generation of agro-ecological homogeneous zones. Alberto Garrido contributed with the insurance design and Paloma with the policy and socio-economic implications of the insurance implementation. Alberto, Ana and Paloma have reviewed and edited the manuscript for obtaining the final version.

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